Interactive Information Retrieval:
Models, Algorithms, and Evaluation

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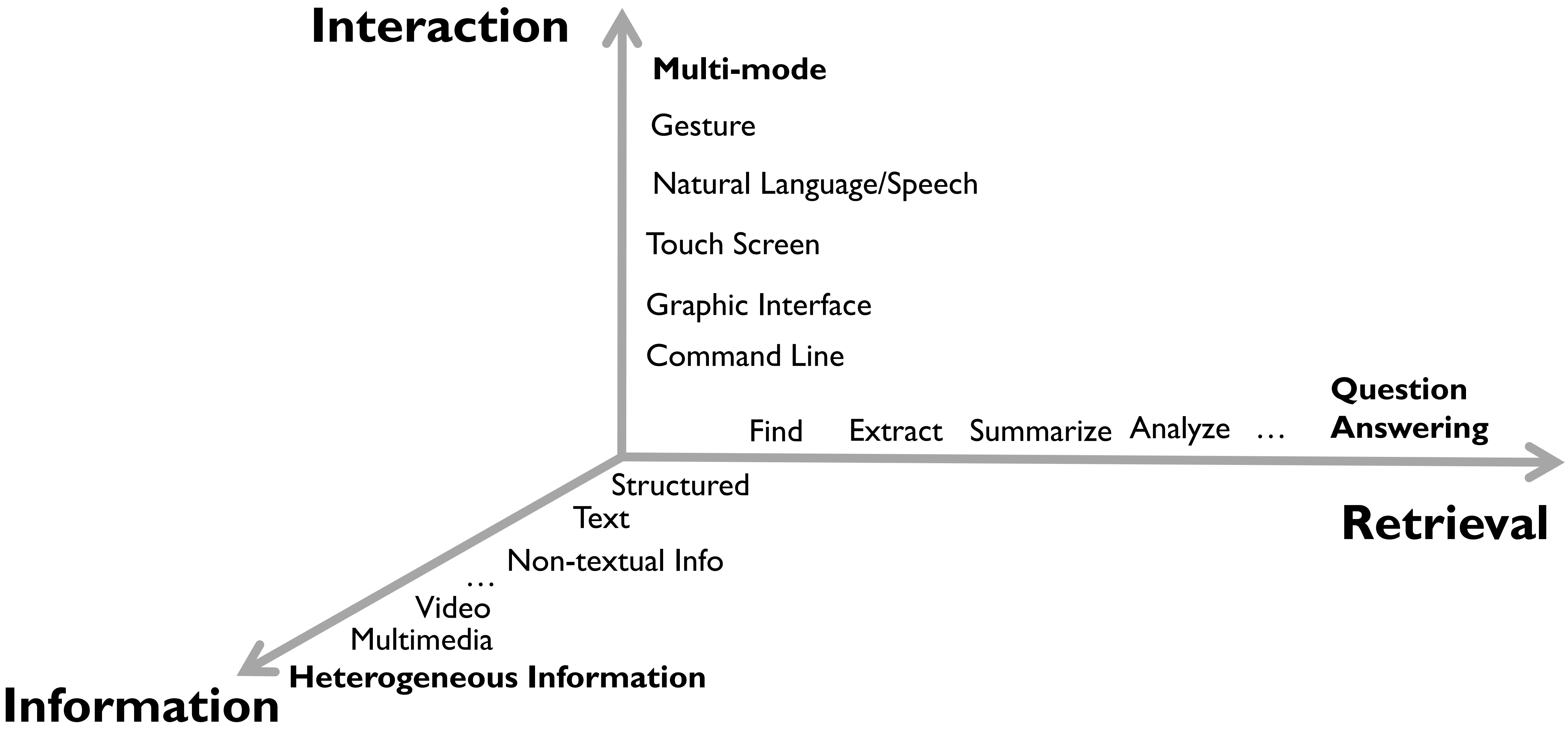
Tutorial at ACM SIGIR 2020, *July 26, 2020*

Outline

- Background
  - What is Interactive Information Retrieval (IIR)?
  - Historical overview of research in IIR
  - Goal of tutorial
- Formal Models for IIR
- Techniques and Algorithms for IIR
- Evaluation of IIR
- Summary

Broad Interpretation of Interactive Information Retrieval



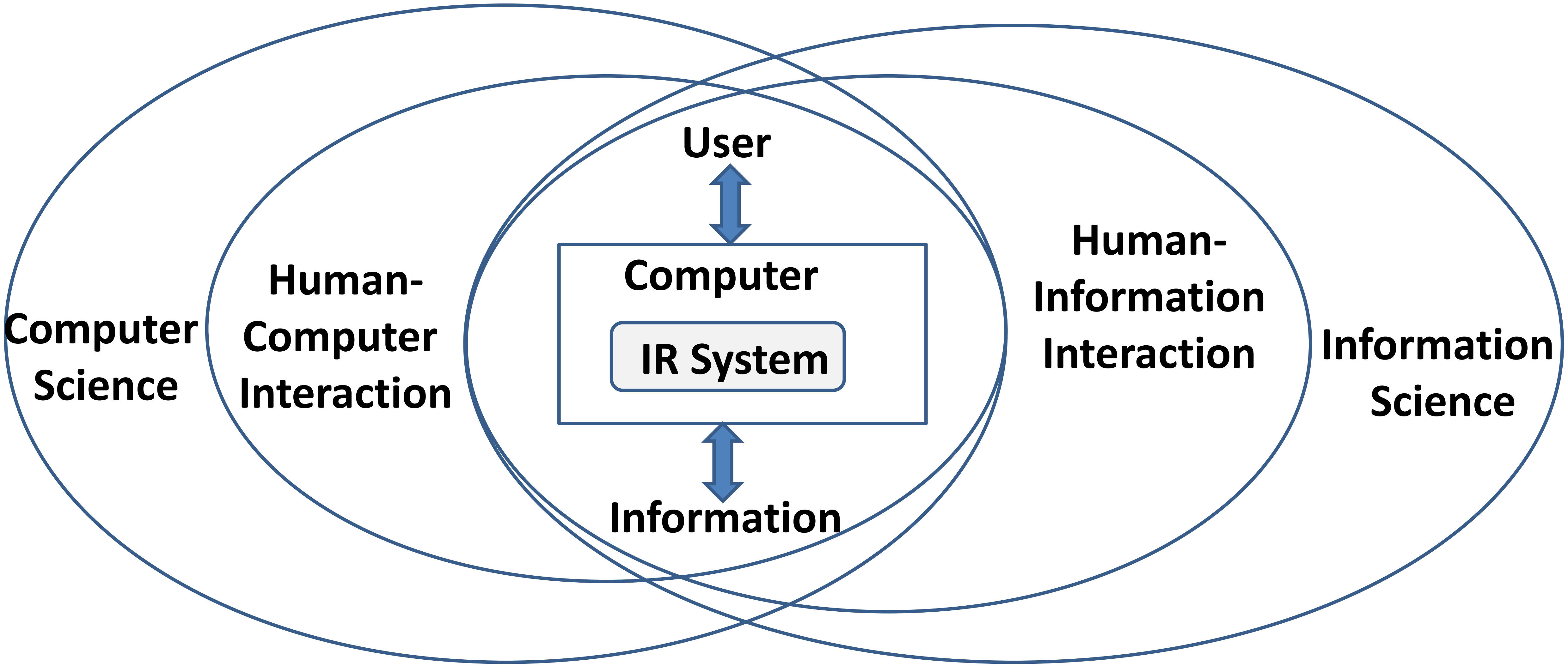
Multiple Perspectives of IIR

- **Cognitive IR framework** (broadest): interactions can be between a person and a system as well as between people

  "... the interactive communication processes that occur during the retrieval of information by involving all the major participants in IR, i.e. the user, the intermediary, and the IR system." Ingwersen, 1992

- **HCI view**: interactions can only be between a person and a system, but the system can go beyond supporting only retrieval to support task and interface can be complex
- **Search engine application view**: interactions are restricted to a search engine interface (iterative query reformulation, browsing, clicking, ...)

IIR as subarea of Computer Science (HCI) and Information Science (HII)



A Historical Overview of Research in IIR

- Computer Science (CS) vs. Information Science (IS): two somewhat disjoint communities
  - "Pure" CS research enabled by "factoring out" users using Cranfield test collections
  - IS research generalizes "information retrieval" to "information seeking," thus not necessarily interactions with a computer
- Inevitable fusion of the two communities
  - Cranfield evaluation methodology does not really measure user satisfaction
  - Information seeking is most often through using a search engine system nowadays

Research in IIR: 1964- Early 1970s

- 1964 MEDLARS: First large-scale (Batch) IR system
- 1972 MEDLINE=MEDLARS Online: First large-scale online IR system
- 1968 Robert Taylor's contribution: 4 information needs + 5 filters
- 1971 Rocchio's contribution: relevance feedback
  - User telling the system which documents are relevant or non-relevant
  - Earliest form of machine support for query reformulation
  - An early supervised learning algorithm
- 1971 Bennett's Design Challenges (an early HCI workshop on IIR): most challenges remain relevant today!

MEDLARS & MEDLINE

- 1964 MEDLARS: First large-scale IR system
  - Search Mode: Batch (multiple queries run together on tapes of indexed medical literature)
  - Users: search specialists from medical school who collaborate with researchers in composing complex queries; manual query reformulation
- 1972 MEDLINE=MEDLARS Online: First large-scale online IR system
  - Search Mode: Online (submit one query and get a response immediately)
  - Users: intermediaries
  - Boolean queries only, command line

Robert Taylor’s Contribution (1968)

- Four levels of information need:
  - Visceral; Conscious; Formal; Compromised
- Five information “filters”
  - Topic; Motivation/Use; Searcher history and characteristics; Match between description and system; Desired answer type
- Based on observation of librarians’ interactions with patrons requiring information (in medical libraries)
- Hypothesis that use of filters leads to “good”results
- Intermediaries educated in technical aspects of searching, and, to some extent, in effective use of filters

Taylor, R.S. (1968) Question-negotiation and information seeking in libraries. College & Research Libraries, 29, 178–194.

Bennett's Design Challenges: Searcher Characteristics

- How can varying levels of user expertise (e.g., casual user through staff member) be supported?
- Can the behavioral characteristics inherent in searchers be correlated with interactive display techniques to give meaning to *ease of use*?
- What level of help should be provided to the user (e.g., online tutorial, staff member demonstration, reference manual, or reference card)?

D.E. Walker (ed.). Interactive bibliographic search: the user/computer interface, AFIPS Press, 1971.

Bennett's Design Challenges: Conceptual Framework

- What is the appropriate level of interaction that should be provided?
- Should the system govern search formulation or should it allow the searcher to construct a search formulation?
- Should the user provide a complete information need statement and await system results?
- Should some combination of these techniques be provided?
- Are Boolean expressions necessary for searching?
- How can the search power of Boolean operations be provided without teaching searchers how to deal with their formalism?
- Under what conditions should feedback be provided?
- How should feedback be implemented?
- How useful are audio and spatial cues to searchers?

Bennett’s Design Challenges: System Evaluation

- How well does the IR system meet user needs?
- What measures can be used to objectively compare different IR systems and different interface features?
- What has been learned from feedback obtained from searchers using currently available systems?

These questions have had significant impact on research in IIR and remain relevant today!

Research in IIR: Middle 1970s – Middle 1980s

- Cognitive View of IIR developed at
  - Royal School of Librarianship, Copenhagen (Jens Rasmussen; Annelise Mark Pejtersen; Peter Ingwersen)
  - University College, London (Nick Belkin, B.C. Brookes)
- Belkin's **Anomalous State of Knowledge** (ASK) hypothesis
  - Inherent inability to specify what one doesn't know.
- B.C. Brookes's Fundamental Equation of Information Science:

$$K(S) + \underbrace{I}_{\text{Information}} = K(S + \underbrace{\Delta S}_{\text{Impact of Information}})$$

Research in IIR: Middle 1970s – Middle 1980s

- Robert N. Oddy's THOMAS (1977)
  - Information retrieval through man-machine dialogue
  - Supporting incremental information seeking through network representation of database
- ASK for information retrieval
  - Combine THOMAS and ASK hypothesis
  - Incremental representation of searcher's ASK through dynamic search session

Suggesting dynamic user modeling!

Research in IIR: Middle 1980s – Early 1990s

- Bates' Berry picking model (1989)
- Ellis' Behavioral model of information seeking strategies (1989)
- Scatter/Gather (Cutting et al. 1992)
- Users shifted to "naïve" end users
  - Lots of effort to make interfaces friendly for end users
  - User modeling for supporting interactive searching
  - Evidence for Taylor's filters; pro and con (see, e.g. Nordlie, 1999)
  - Complex experimental systems were built, e.g. Vickery & Brooks, 1987
  - Systems which observe search behavior in order to offer new types of tailored support (Meadow, Hewitt & Aversa, 1982)
- Okapi system (Steve Walker, Natalie Mitev, Steve Robertson)
  - Implementing Probability Ranking Principle in an IIR framework

Research in IIR: Middle 1990s – Present

- The Web era! Web as a digital library
  - Users shifted to ordinary people
  - Task as a fundamental concept in IIR (Typology of queries, lookup vs. exploratory)
  - Extension of Ellis' model by Meho & Tibbo (2003), Marchionini's search task taxonomy (2006)
- TREC tasks have played a significant role in shaping IR research
  - Interactive Track (lasted for 12 years)
- Machine learning and data mining applied to research in IIR
  - Learning from implicit feedback/search log
  - Analysis of search log data
- A/B test for evaluation of IIR
- Formal models and algorithms developed for IIR
- Mobile search, conversational search, …
- Simulation-based evaluation of IIR

Goal of the Tutorial

- Focuses more on recent progress (after 2000)
- Attempts to be broad, at the cost of sacrificing depth
- Emphasizes general framework, formal models, and general algorithms
- What is not covered
  - Many specific systems and ideas of interface design (see, e.g., [Hearst 09])
  - Details of many specific models and machine learning algorithms (see, e.g., [Gao et al. 19])

Marti A. Hearst. 2009. ***Search User Interfaces*** (1st ed.). Cambridge University Press, New York, NY, USA. https://searchuserinterfaces.com/

Jianfeng Gao, Michel Galley and Lihong Li (2019), "**Neural Approaches to Conversational AI**", *Foundations and Trends in Information Retrieval*: Vol. 13: No. 2-3, pp 127-298. http://dx.doi.org/10.1561/1500000074

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- Formal Models for IIR
  - A cooperative game framework for IIR
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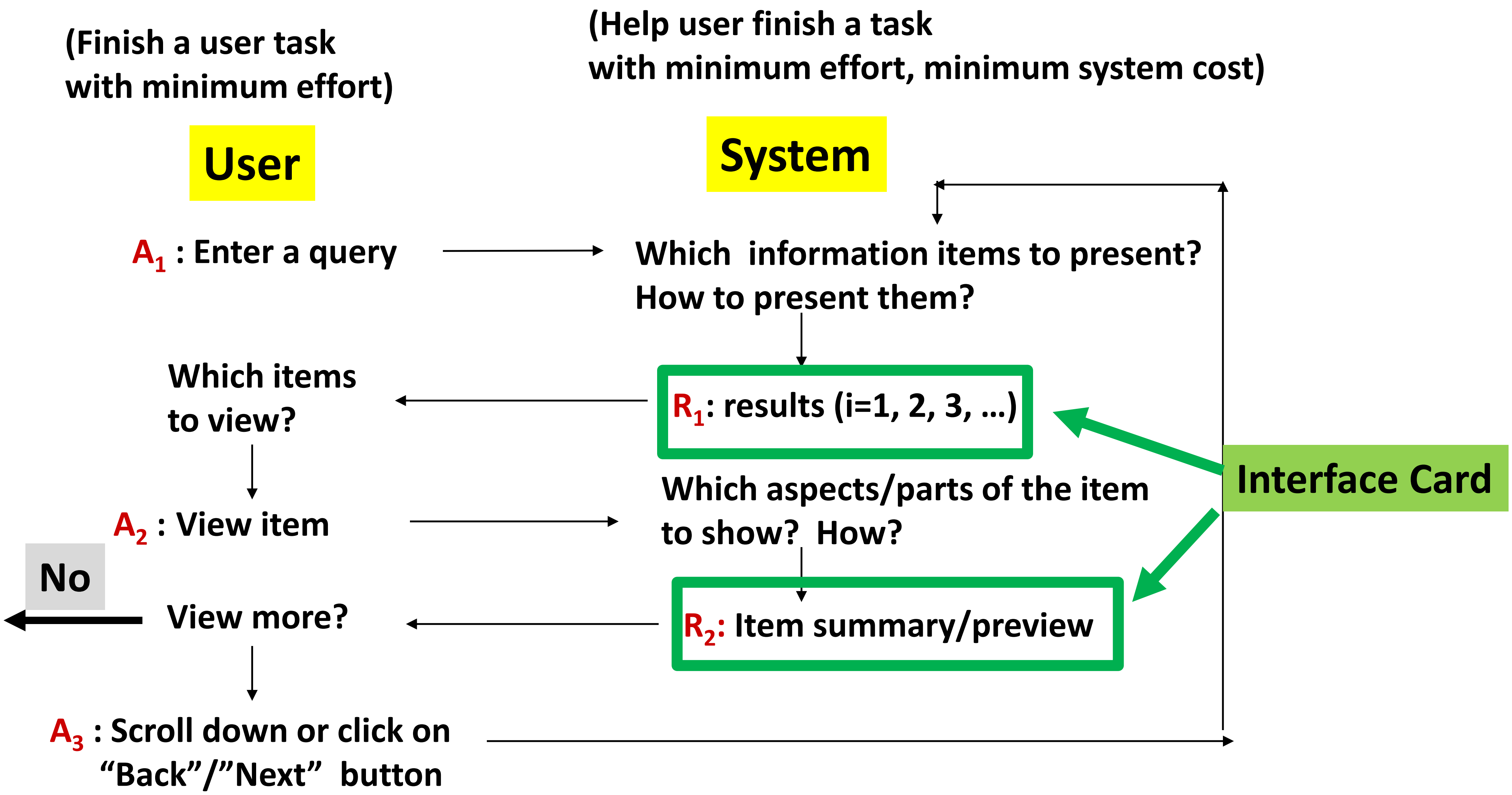
Interactive IR = Cooperative Game-Playing

- Retrieval process = cooperative game-playing
- **Players**: Player 1= search engine; Player 2= user
- **Rules** of game:
  - Player take turns to make “moves”
  - First move = “user entering the query” (in search) or “system recommending information” (in recommendation)
  - User makes the last move (usually)
  - For each move of the user, the system makes a response move (shows an interaction interface), and vice versa
- **Objective**: help the user complete the (information seeking) task with minimum effort & minimum operating cost for search engine

Unification of search and recommendation

Cooperative game-playing with Interface Cards



Major benefits of IR as game playing

- **General**
  - A formal framework to **integrate research** in user studies, evaluation, retrieval models, and efficient implementation of IR systems
  - A general roadmap for identifying **unexplored important research topics in Interactive IR**
- **Specific**
  - Naturally optimize performance on an entire session instead of that on a single query (optimizing the chance of winning the entire game)
  - Optimize the collaboration of machines and users (maximizing collective intelligence) [Belkin 96]
  - Emphasize the two-way communications between a user and a system (e.g., active feedback)
  - …

4 Key Elements of the IR Game Framework (4 C's)

- **Collaboration**: Optimization of the collaboration (or **combined intelligence**, combined performance) of a user and a system
  - User knows well about what's useful, but doesn't know the whole information space
  - System "sees" the whole information space, but doesn't know which is most useful
- **Communication**: Optimization of the **two-way communications** between a user and a system
  - Communication of the shared goal and plan
  - Explanation of both user actions and system responses
- **Cognition:** Optimization of cognition for user (ASK theory, **bridge the cognition gap**) and system (**machine learning**)
  - Modeling of knowledge state and helping users learn during search
  - Helping system learn knowledge about tasks and relevance
- **Cost:** Optimization of system operation cost
  - Modeling operation cost and providing **cost-effective responses**

Formalization of the IR Game

Given S, U, C, A_t , and H, choose the best R_t from all possible responses to A_t

Situation **S**

History **H={(A_i,R_i)}** i=1, …, t-1

User **U**: A_1 A_2 … … A_{t-1} **A_t**

System: R_1 R_2 … … R_{t-1} **R_t =?**

Query="light laptop"

Click on "Next" button

The best ranking for the query

The best ranking of unseen items

Best interface!

$R_t \in r(A_t)$

All possible rankings of items in C

All possible rankings of unseen items

All possible interfaces

C

Info Item Collection

Bayesian Decision Theory for **Optimal Interactive Retrieval** [Zhai 2016]

Observed

Situation:	**S**
User:	**U**
Interaction history:	**H**
Current user action:	$\mathbf{A_t}$
Document collection:	**C**

User Model

$M=(K, \theta_U, B, T, \ldots)$

Knowledge State (seen items, readability level, …)

Information need

Browsing behavior

Task

All possible responses:

$\mathbf{r(A_t)=\{r_1, \ldots, r_n\}}$

$L(r_i, M, S)$

Loss Function

Optimal response: r* (minimum loss)

$$R_t = \arg\min_{r \in r(A_t)} \int_M L(r, \underline{M}, S)\, p(\underline{M} \mid \underline{U, H, A_t, C, S})\, dM$$

Bayes risk **Inferred** **Observed**

ChengXiang Zhai. Towards a game-theoretic framework for text data retrieval, IEEE Data Eng. Bull. 39(3): 51-62 (2016).

An extension of risk minimization [Zhai & Lafferty 06, Shen et al. 05]

Simplification of Computation

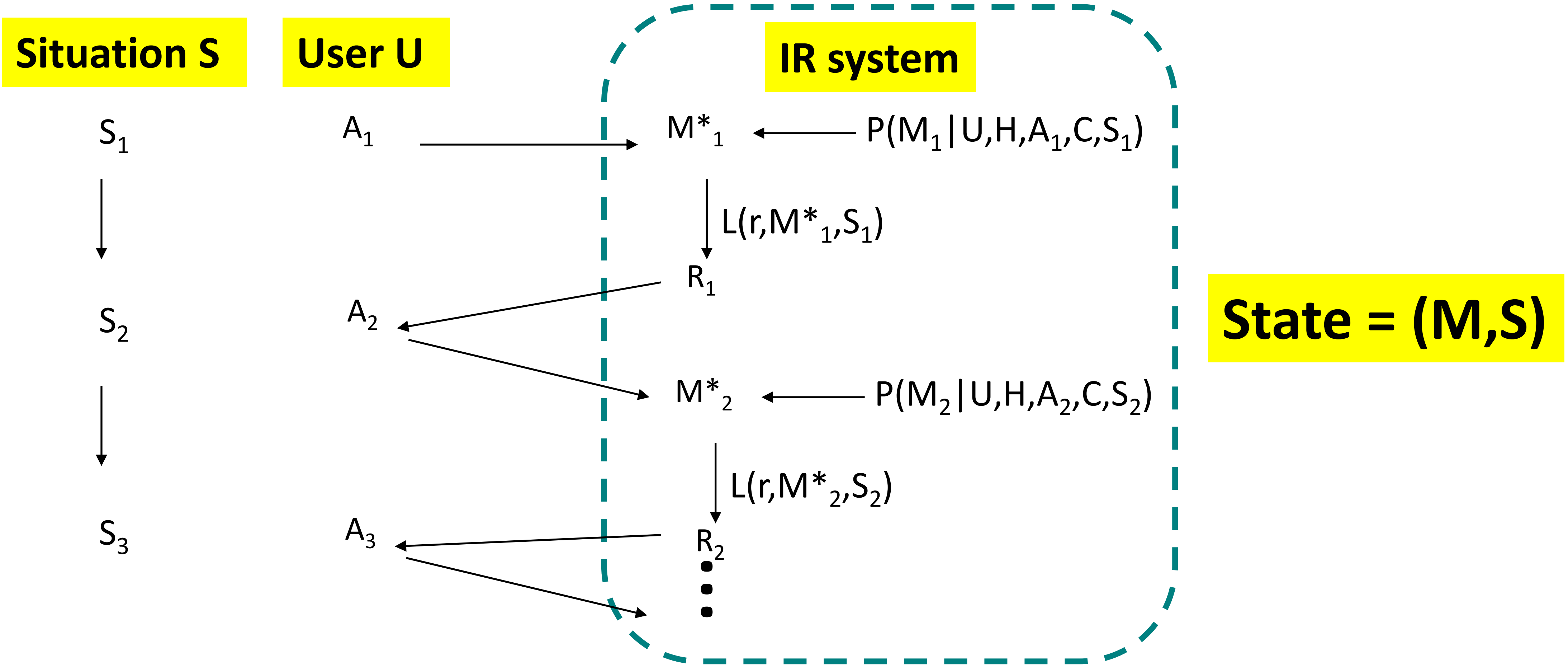
- Approximate the Bayes risk (posterior mode)

$$
\begin{aligned}
R_t &= \arg\min_{r \in r(A_t)} \boxed{\int_M} L(r, M, S) p(M \mid U, H, A_t, C, S) dM \\
&\approx \arg\min_{r \in r(A_t)} L(r, M^*, S) \underline{p(M^* \mid U, H, A_t, C, S)} \\
&= \arg\min_{r \in r(A_t)} L(r, M^*, S)
\end{aligned}
$$

$$\text{where} \quad M^* = \arg\max_M p(M \mid U, H, A_t, C, S)$$

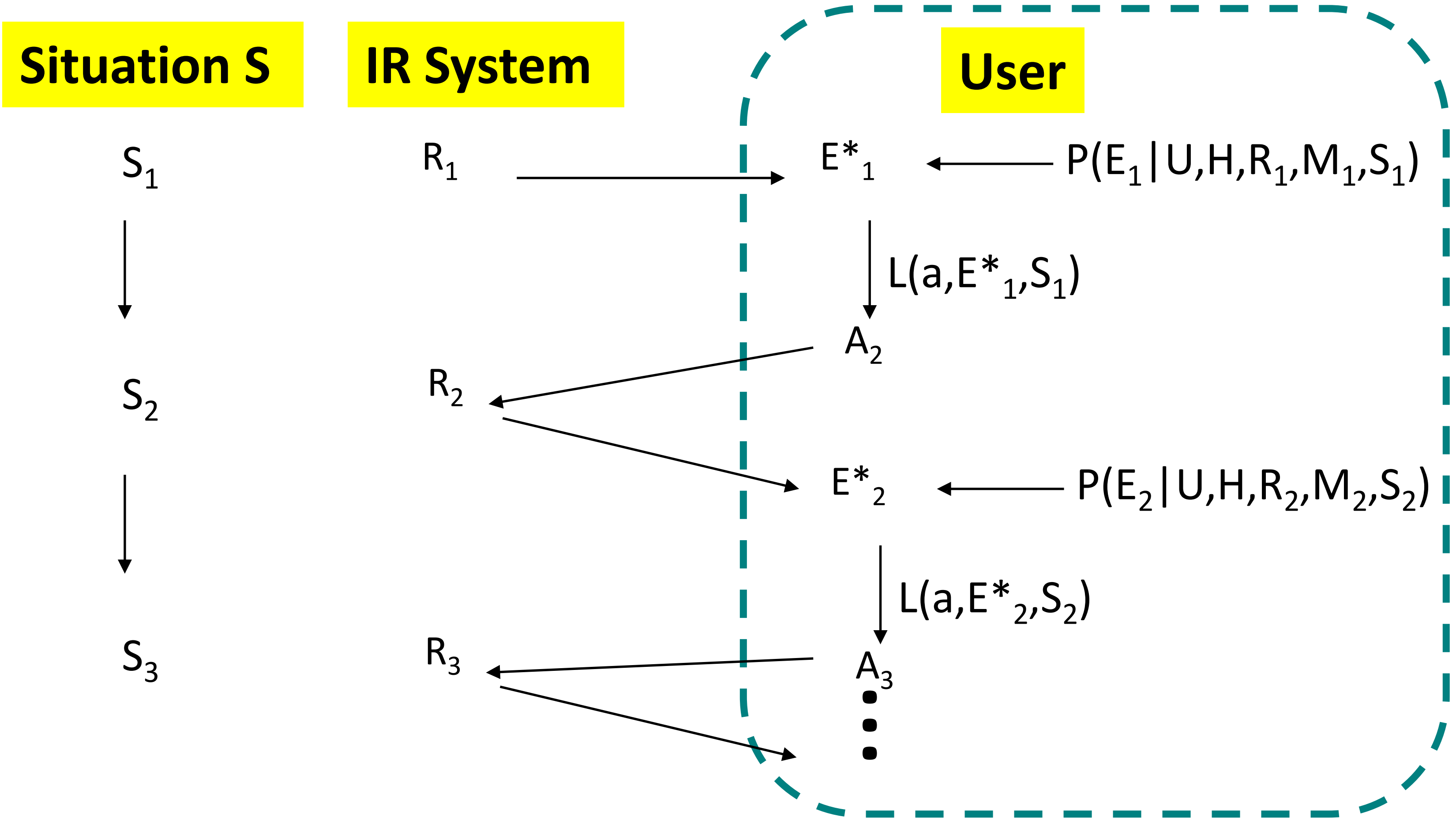
- Two-step procedure
  - Step 1: Compute an updated user model M* based on the currently available information
  - Step 2: Given M*, choose an optimal response to minimize the loss function

Optimal Interactive Retrieval



System's decision process can be modeled by a Partially Observable Markov Decision Process (POMDP) with (M, S) as State

Duality of User & System Decision Making



Retrieval environment
E= (Collection, SearchSystem)

State = (E,S)

User's decision process (behavior) can be modeled by a POMDP as well with (E,S) as State

Instantiation of IR Game

- **Situation S**: can include time, location, and other environmental factors that are relevant to a task
- **Document Collection C:** naturally available in any application
- **User U**: can include any information we know about a user (or group)
- **User interaction history H:** naturally accumulated over time
- **User Actions** and **System Responses R(A)**: all interfaces (moves of the game)
- **Loss Function L(R,M,S):** captures the objective of the game
- **User Model M**: can include everything that we can infer about a user relevant to deciding how to respond to a user's action
- **Inference of User Model P(M|U, H, At, C,S):** capture system's belief about user model M

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Instantiation of IR Game: Moves (Interface Design)

- User moves: Interactions can be modeled at different levels
  - Low level: keyboard input, mouse clicking & movement, eye-tracking
  - Medium level: query input, result examination, next page button
  - High level: each query session as one "move" of a user
- System moves: can be enriched via sophisticated interfaces, e.g.,
  - User action = "input one character" in the query: System response = query completion
  - User action = "scrolling down": System response = adaptive summary
  - User action = "entering a query": System response = recommending related queries
  - User action = "entering a query": System response = ask a clarification question

Example of new moves (new interface): Explanatory Feedback

- Optimize combined intelligence →
  - Leverage human intelligence to help search engines
- Add new "moves" to allow a user to help a search engine with minimum effort
- Explanatory feedback
  - I want documents similar to this one except for not matching "X" (user typing in "X")
  - I want documents similar to this one, but also further matching "Y" (user typing in "Y")
  - …

Instantiation of IR Game: User Model M

- **M = formal user model capturing essential knowledge about a user's state for optimizing system moves**
  - Essential component: θ_U = user's current information need
  - K = knowledge state (seen items)
  - Readability level
  - T= task
  - Patience-level
  - B= User behavior
  - Potentially include all findings from user studies!
- **An attempt to <u>formalize</u> existing models such as**
  - Anomalous State of Knowledge (ASK) [Belkin 80, Belkin et al. 82]
  - Cognitive IR Theory [Ingwersen 96]

Instantiation of IR Game: Inference of User Model

- P(M|U, H, At, C,S) = system's current belief about user model M
  - Enables inference of the formal user model M based on everything the system has available so far about the user and his/her interactions
- Instantiation can be based on
  - Findings from user studies, and
  - Machine learning using user interaction log data for training
- Much work has been done on estimating/updating the information need θ_U and clicking behavior (e.g., implicit feedback [Joachims et al. 05, Shen et al. 05], intent understanding [Liu et al. 11], and many click models [Chuklin et al. 15, Liu et al. 17])
- Some work on inferring/updating other variables about the user, e.g.,
  - reading level [Collins-Thompson et al. 11]
  - modeling decision point [Thomas et al. 14]

Instantiation of IR Game: Loss Function

- L(Rt ,M,S): loss function **combines** measures of
  - **Utility of Rt** for a user modeled as M to **finish the task** in situation S
  - **Effort of a user** modeled as M in situation S
  - **Cost of system** performing Rt (connected with **efficiency of IR systems** [Witten et al. 99])
- Tradeoff varies across users and situations
- **Utility of Rt** is a **sum** of
  - **ImmediateUtility(Rt)** and
  - **FutureUtilityFromInteraction(Rt)**, which depends on user's interaction behavior

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Instantiation of IR Game: Loss Function (cont.)

- Formalization of utility depends on research on evaluation, task modeling, and user behavior modeling
- Traditional evaluation measures tend to use
  - Very simple user behavior model (sequential browsing)
  - Straightforward combination of effort and utility
- They need to be extended to incorporate **more sophisticated user behavior models** (e.g., [de Vries et al. 04] , [Smucker & Clarke 12], [Baskaya et al. 13])
- Much progress has been made recently on **incorporating click models** (simple user interaction models) into a loss function for **learning to rank or recommend** (e.g., online learning to rank [Hofmann et al. 11] , dynamic IR [Yang et al. 06], recommendation [Zhao et al. 08], sequential browsing [Wei et al. 17])

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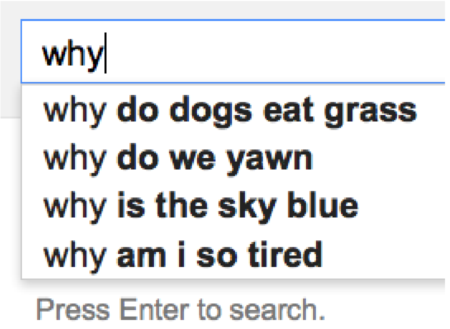
Example of Instantiation: Information Card Model (ICM) [Zhang & Zhai 15, Zhang & Zhai 16]

How to optimize the interface design?



… or a combination of some of these?

How to allocate screen space among different blocks?

Yinan Zhang, ChengXiang Zhai, Information Retrieval as Card Playing: A Formal Model for Optimizing Interactive Retrieval Interface, *Proceedings of ACM SIGIR 2015.*
Yinan Zhang and Chengxiang Zhai. 2016. A Sequential Decision Formulation of the Interface Card Model for Interactive IR. In *Proceedings of ACM SIGIR 2016.*

Optimal User Interface = Optimal “Card Playing”

- In each interaction *lap*
- … facing an (evolving) interaction *context*
- … the system tries to play a *card*
- … that optimizes the user’s *expected surplus*
- … based on the user’s *action model* and *reward* / *cost* estimates
- … given all the *constraints* on card

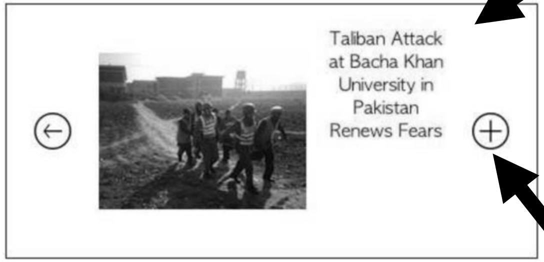
Example of interface optimization

Context c^t

After a user clicks on "Colleges & Universities", which interface card q^t to show?

If showing card q^t

If user action a^{t+1}= view content



surplus for a^{t+1} :

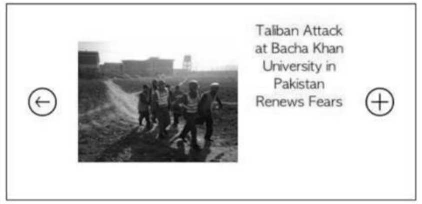
$$u(a^{t+1} \mid q^t, c^t) = \text{gain} - \text{cost}$$

If user action a^{t+1}= "see more"?

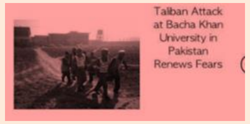
A different card

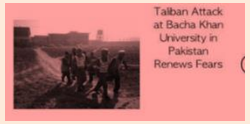
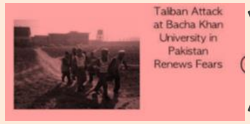
If user action a^{t+1}= "navigate"?

Expected surplus of an interface card: $E(u^t|q^t,c^t)$

$E(u^t\,|\,q^t =$  $,c^t)$

$=p(\,a^t=$"view content" $|c^t,q^t) \times u($  $|\,c^t,q^t)$

$u($  $|\,c^t,q^t) =$ Gain () – Cost(Viewing)

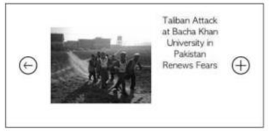
Gain ()=Relevance()

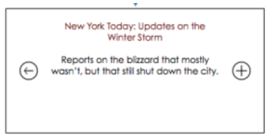
$+\ p(\,a^t=$"see more" $|c^t,q^t) \times u($  $|\,c^t,q^t)$ + …

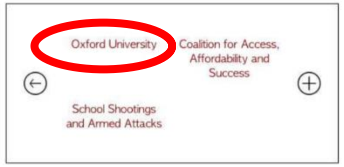
Depends on the next interface card q^{t+1}

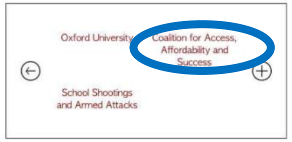
Expected surplus of an interface card: $E(u^t|q^t,c^t)$

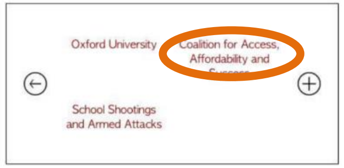
$E(u^t\,|\,q^t =$  $,c^t)$





$= p(\,a^t =$ "left-top tag" $|\,c^t, q^t) \times u($  $|\, c^t, q^t)$

$+\ p(\,a^t =$ "right-top tag" $|\,c^t, q^t) \times u($  $|\, c^t, q^t)$

$+\ p(\,a^t =$ "left-bottom tag" $|\,c^t, q^t) \times u($  $|\, c^t, q^t)$

$+ \ldots$

ICM: Formal Definition

$$\begin{aligned}
\underset{q^t}{\text{maximize}} \quad & E(u^t|c^t, q^t) \\
&= \sum_{a^{t+1} \in \mathcal{A}(q^t)} p(a^{t+1}|c^t, q^t)\, u(a^{t+1}|c^t, q^t) \\
\text{subject to} \quad & f_c^t(q^t) \leq 0
\end{aligned}$$

Interface card

$$\underset{\boxed{q^t}}{\text{maximize}} \quad E(u^t|c^t, q^t)$$

$$= \sum_{a^{t+1} \in \mathcal{A}(q^t)} p(a^{t+1}|c^t, q^t)\, u(a^{t+1}|c^t, q^t)$$

$$\text{subject to} \quad f_c^t(q^t) \leq 0$$

Context

$$
\begin{aligned}
\underset{q^t}{\text{maximize}} \quad & E(u^t \boxed{| c^t,}\, q^t) \\
& = \sum_{a^{t+1} \in \mathcal{A}(q^t)} p(a^{t+1} \boxed{| c^t,}\, q^t)\, u(a^{t+1} \boxed{| c^t,}\, q^t) \\
\text{subject to} \quad & f_c^t(q^t) \leq 0
\end{aligned}
$$

$$
\begin{aligned}
\underset{q^t}{\text{maximize}} \quad & E(u^t|c^t, q^t) \\
& = \sum_{a^{t+1} \in \boxed{\mathcal{A}(q^t)}} p(a^{t+1}|c^t, q^t)\, u(a^{t+1}|c^t, q^t) \\
\text{subject to} \quad & f_c^t(q^t) \leq 0
\end{aligned}
$$

Action set

$$\begin{aligned}
\underset{q^t}{\text{maximize}} \quad & E(u^t|c^t, q^t) \\
&= \sum_{a^{t+1} \in \mathcal{A}(q^t)} \boxed{p(a^{t+1}|c^t, q^t)}\, u(a^{t+1}|c^t, q^t) \\
\text{subject to} \quad & f_c^t(q^t) \leq 0
\end{aligned}$$

Action model

Reward $\qquad$ Cost

$$r(a^{t+1}|c^t, q^t) - s(a^{t+1}|c^t, q^t)$$

$$\begin{aligned}
\underset{q^t}{\text{maximize}} \quad & E(u^t|c^t, q^t) \\
& = \sum_{a^{t+1} \in \mathcal{A}(q^t)} p(a^{t+1}|c^t, q^t)\, \boxed{u(a^{t+1}|c^t, q^t)} \\
\text{subject to} \quad & f_c^t(q^t) \leq 0
\end{aligned}$$

Action surplus

Expected surplus

$$\underset{q^t}{\text{maximize}} \quad \boxed{E(u^t|c^t, q^t)}$$

$$= \sum_{a^{t+1} \in \mathcal{A}(q^t)} p(a^{t+1}|c^t, q^t)\, u(a^{t+1}|c^t, q^t)$$

$$\text{subject to} \quad f_c^t(q^t) \leq 0$$

$$
\begin{aligned}
\underset{q^t}{\text{maximize}} \quad & E(u^t|c^t, q^t) \\
& = \sum_{a^{t+1} \in \mathcal{A}(q^t)} p(a^{t+1}|c^t, q^t)\, u(a^{t+1}|c^t, q^t) \\
\text{subject to} \quad & \boxed{f_c^t(q^t) \leq 0}
\end{aligned}
$$

Constraint(s)

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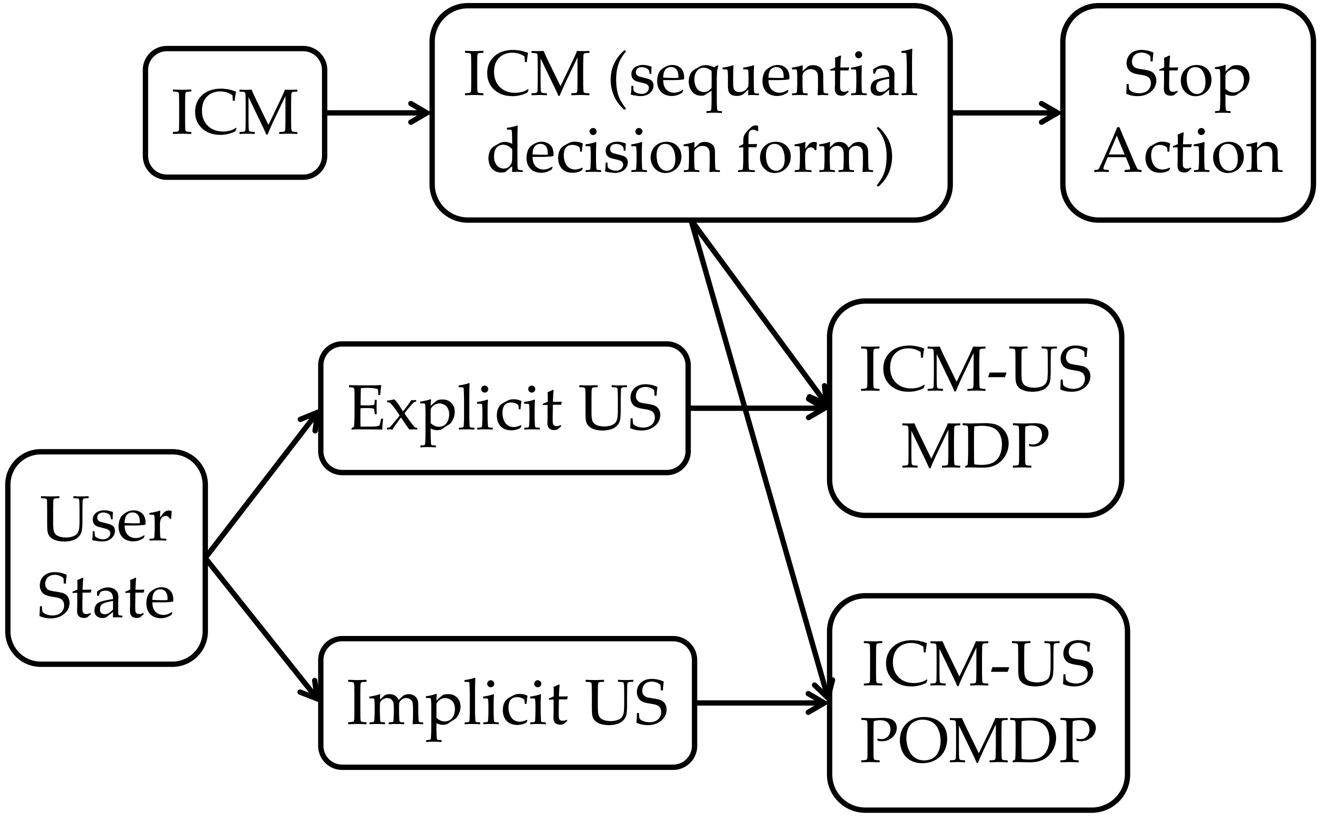
Refinements/Instantiations of ICM



ICM-US model

- MDP form:

$$E(u^t|z^t) = \max_{q^t} \sum_{z^{t+1}} \Big(p(z^{t+1}|z^t, q^t) \cdot$$

$$\big(u_0(z^t, q^t, z^{t+1}) + E(u^{t+1}|z^{t+1})\big) \Big)$$

- POMDP form:

$$E(u^t|d^t) = \max_{q^t} \sum_{a^{t+1} \in \mathcal{A}(q^t)} \Big(p(a^{t+1}|d^t, q^t) \cdot$$

$$\big(u_0(d^t, q^t, a^{t+1}) + E(u^{t+1}|d^{t+1})\big) \Big)$$

Stop action model

- An ordinary user action
  - Stopping rate: $p(a_B^{t+1}|c^t, q^t)$
  - Zero expected future surplus:

$$E(u^{t+1}|c^{t+1}) = 0, \text{ where } c^{t+1} = (c^t, q^t, a_B^{t+1})$$

- Constant stopping rate (CSR)

$$\beta^0 = p(a_B^{t+1}|c^0) = p(a_B^{t+1}|c^t, q^t), \forall c^t, q^t, 0 < \beta^0 < 1$$

CSR => diminishing reward

$$E(u^t|c^t) = \max_{q^t}\Big(u_0(c^t, q^t) +$$

$$\boxed{(1-\beta^0)} \sum_{a^{t+1} \neq a_B^{t+1}} p_K^t(a^{t+1}|c^t, q^t)\, E(u^{t+1}|c^{t+1})\Big)$$

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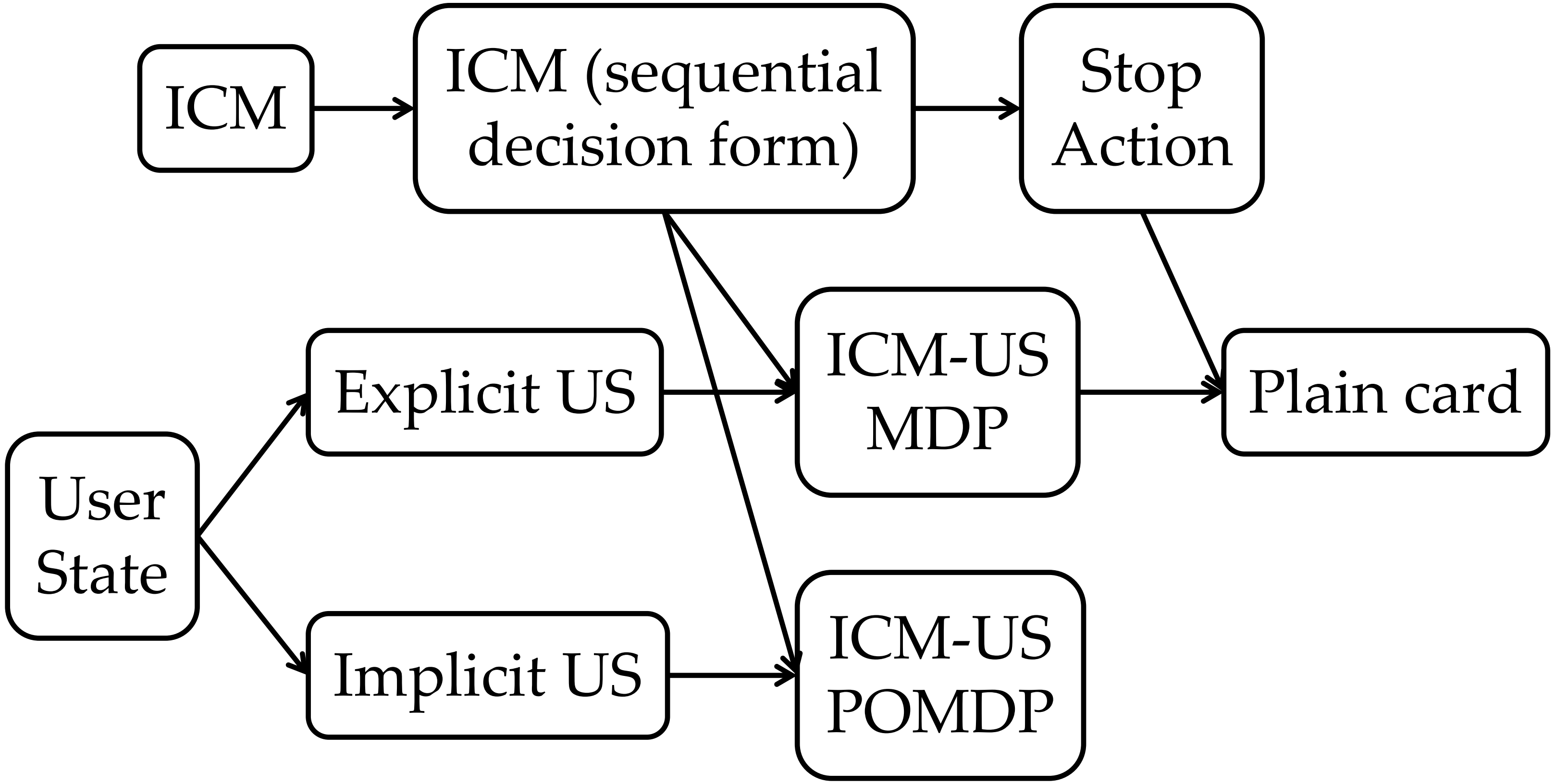
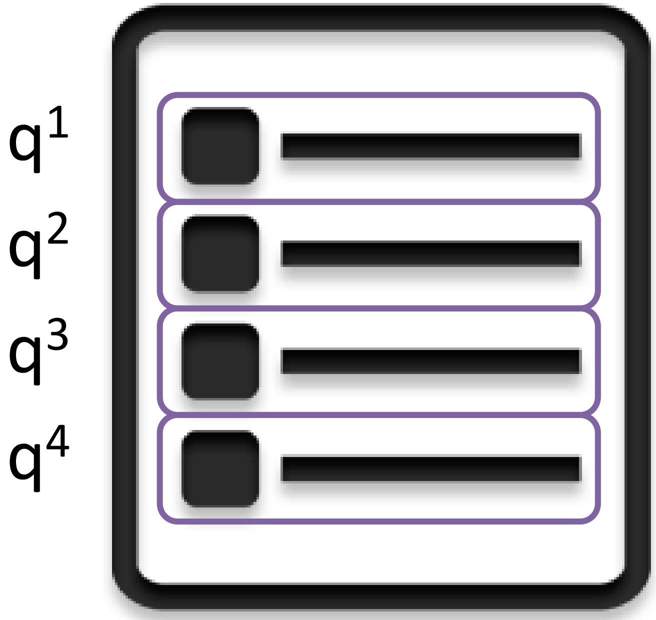
ICM for Interactive Retrieval Optimization: Plain Card



PLAIN CARD (IIR-PRP)

“Backward compatibility”

- If we assume sequential interaction reduces to sequential browsing …



Instantiation

- Card: a choice in a ranked list
- Constraint: none
- Action: accept / skip a choice
- Context: constant until an accept
- Reward (for skip): expected surplus in next lap
- Cost: decision cost

Plain card

- Plain user state

$$z^t = \{e : q^{t'} \neq e, \forall t' < t\}$$

- Assume CSR
- Ranking principle

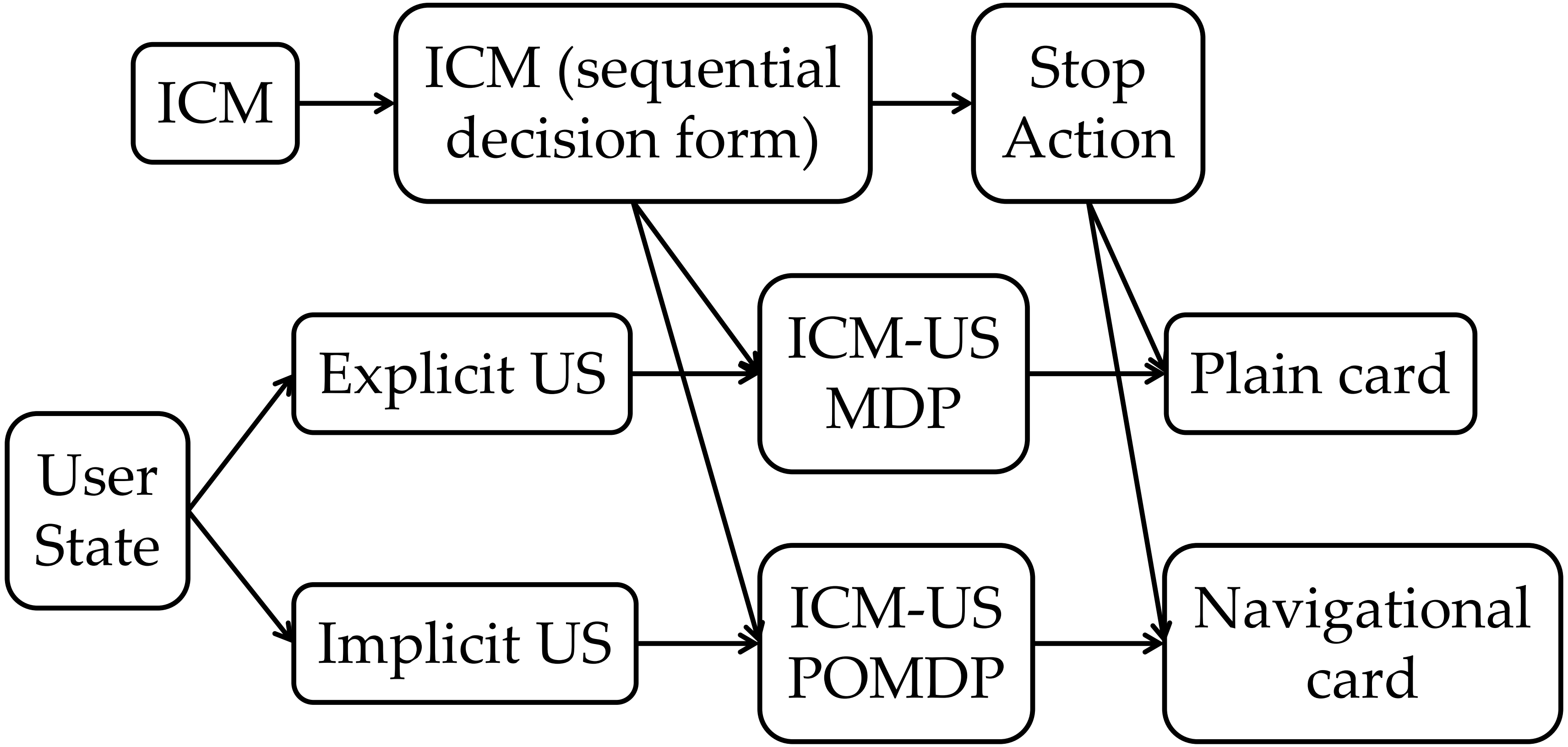
$$\eta(e) = \boxed{\frac{p(e)}{p(e) + \beta^0}} \boxed{\left(r(e) - \frac{s(e)}{p(e)}\right)}$$

Further promote more relevant items

Interactive IR- Prob. Ranking Principle (IIR-PRP)

Norbert Fuhr. 2008. A probability ranking principle for interactive information retrieval. *Inf. Retr.* 11, 3 (June 2008), 251-265. DOI=http://dx.doi.org/10.1007/s10791-008-9045-0

ICM for Interactive Retrieval Optimization: Navigational Card



NAVIGATIONAL CARD

What IIR-PRP cannot do …

- If <u>sequential interaction</u> does *not* reduce to <u>sequential browsing</u> (e.g. on mobile screen) …

Instantiation

- Card: a set of item/tag blocks
- Constraint: total area does not exceed the card
- Action: select block based on item-tag relations
- Context: updated based on user actions
- Reward: information gain of user interest estimate
- Cost: constant for each lap

Analytical Study

- Goal
  - Derive the optimal mathematical conditions for the blocks on the card
- Assumptions
  - Uniform initial preference
  - Uniform and perfect action model
  - Only focus on tags (items would be more trivial)
  - “Complete” tag set

One tag per card

$$w(b) = 1, \forall\, b$$

Balanced partition

What is the optimal number of items the picked tag should cover?

$$\underset{x}{\text{minimize}} \quad \frac{1}{n}\left(x \log x + (n-x)\log(n-x)\right)$$

$$x = \frac{n}{2}$$

Two tags per card

$w(b) = 1/2, \forall\, b$

Balanced partition

Minimal overlap

(a) How many items should each of the two picked tags cover?
(b) How many items should the two tags' coverage overlap?

$$\underset{x,y,t}{\text{minimize}} \quad \frac{1}{n}\Big(t \log 2 + (x - \frac{t}{2}) \log (x - \frac{t}{2}) + (y - \frac{t}{2}) \log (y - \frac{t}{2}) + (n - x - y + t) \log (n - x - y + t)\Big)$$

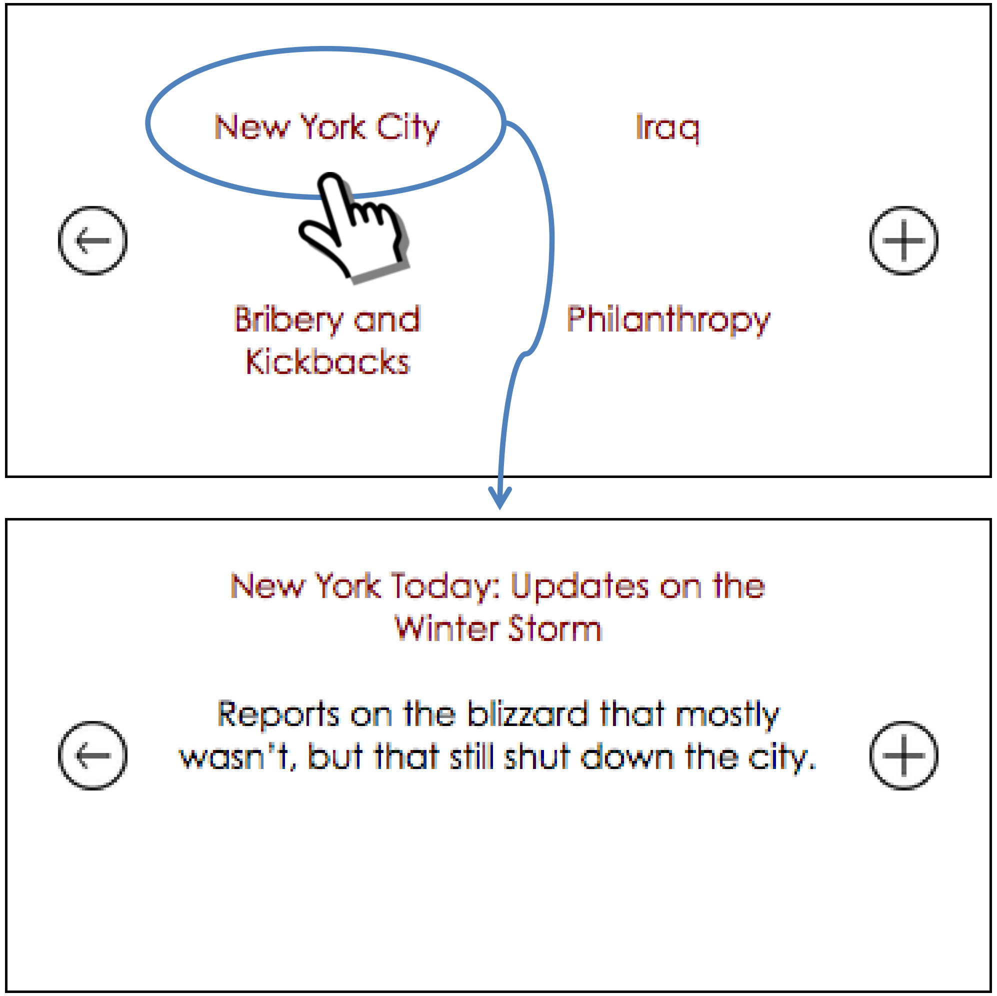
$$x = y = \frac{n}{3}$$
$$t = 0$$

User study experiments

- Setting
  - Prototype interfaces for New York Times
  - Articles as items and keywords as tags
  - Two sizes: a medium sized one and a small one
- Comparison
  - # Interaction rounds to reach item of interest
  - We *automatically* optimize the interface layout
  - Compare with pre-designed static interfaces

Medium sized screen

Smaller screen



Interaction round comparison

More beneficial when screen is small and number of items large

Table 1: Significance levels of comparison results.

Card size	Item set size	Valid sample size	P-value
Small	20	19	**0.004753**
Small	50	23	**0.0003546**
Medium	20	18	0.09183
Medium	50	20	**0.01097**

http://timan102.cs.illinois.edu/yzhng103/fomalhaut/s-times-navigation.php
http://timan102.cs.illinois.edu/yzhng103/fomalhaut/m-times-navigation.php

Adaptation to user stopping tendency

- User stop action: zero expected future surplus
- User interest state: the user's interested item
  - Hidden; does not change across laps
- Variables to examine in experiments
  - Screen size: S = Small; M = Medium
  - User patience level: P = Patient; I = Impatient
- Simulation experiments
- User study experiments

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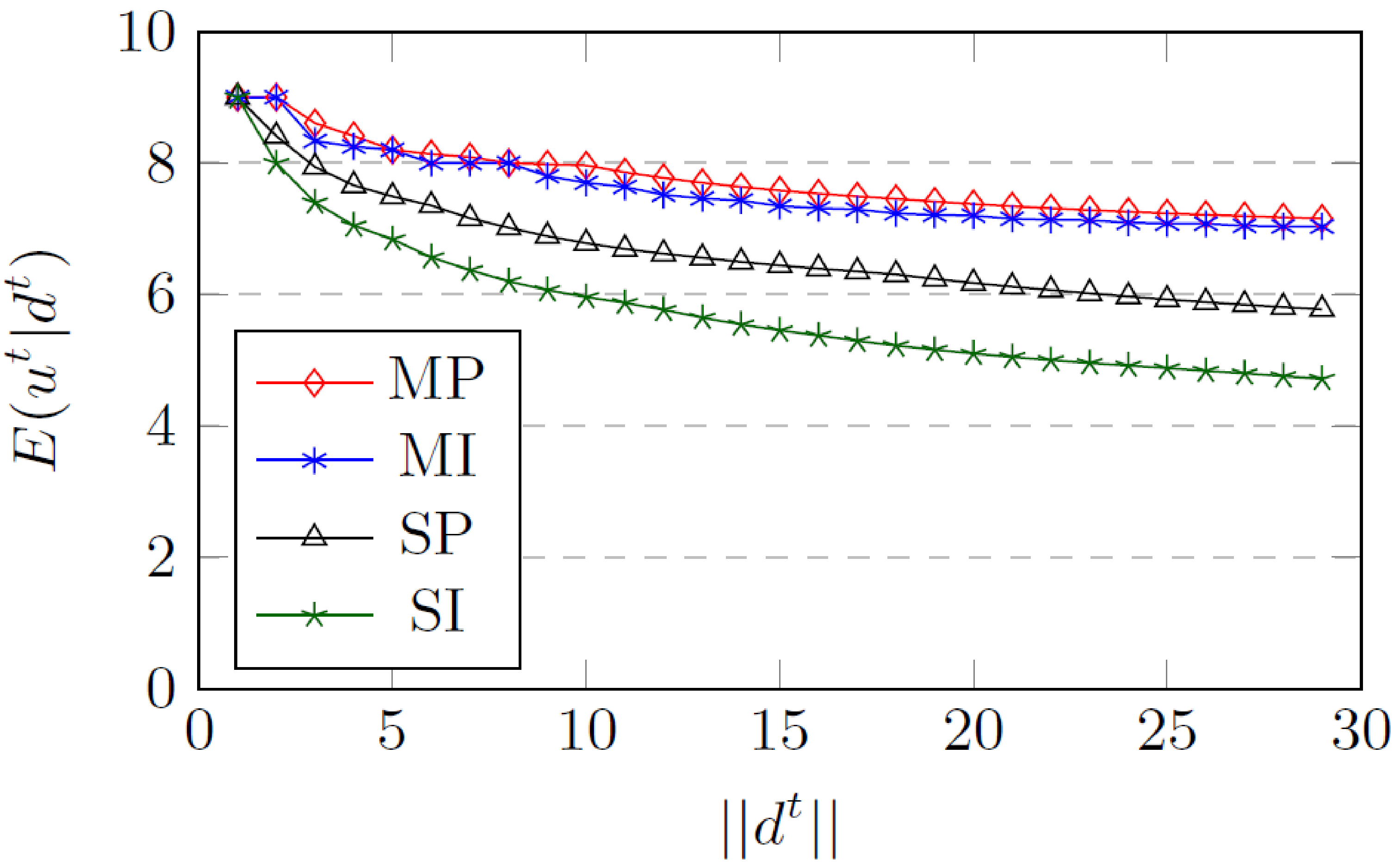
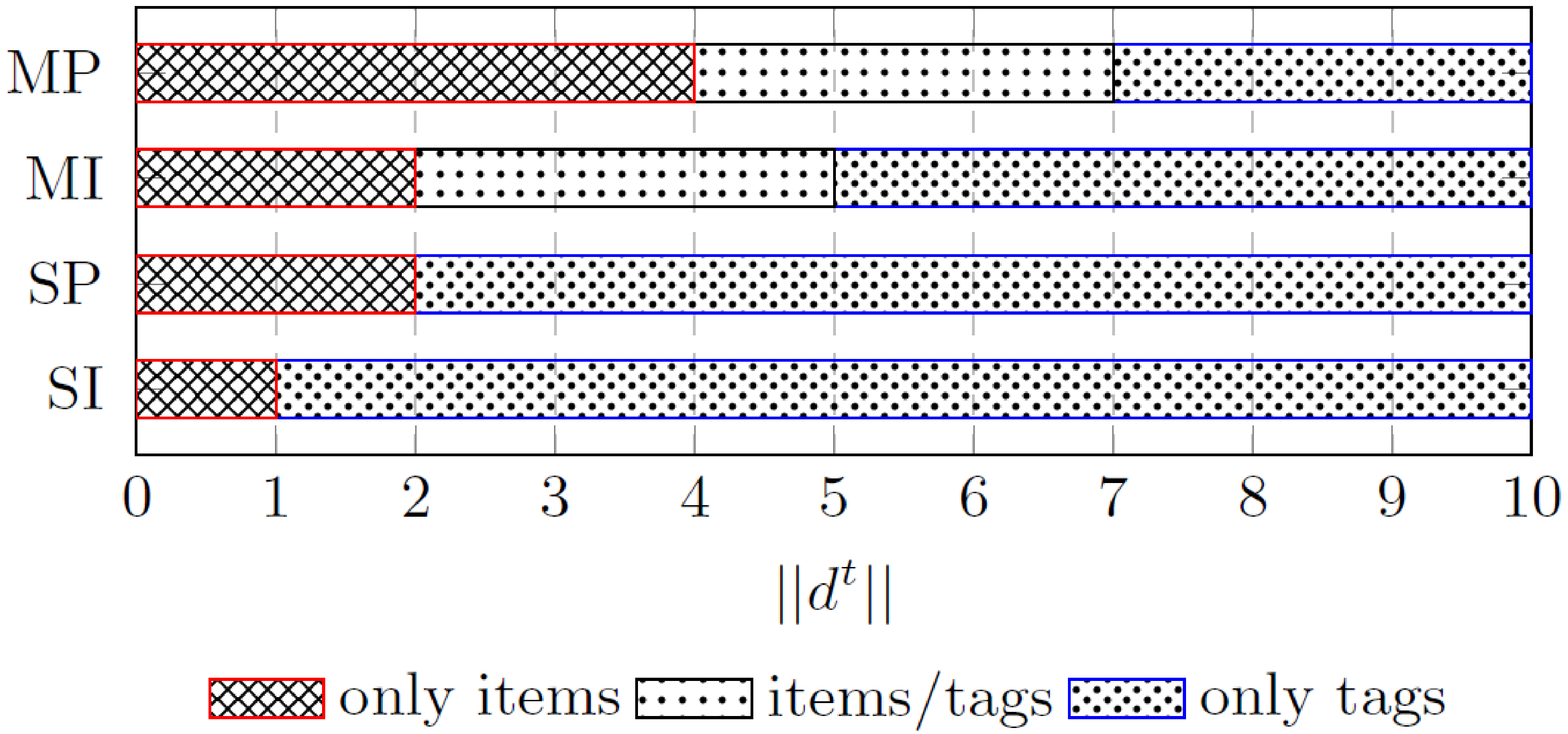
Simulation experiments

Figure 1: Value function of belief states



Simulation experiments

Figure 2: Optimal policy for belief states



Additional user study experiments

Table 1: Significance levels of comparison tests.

Setting	Sample size	"Success?"	"#lap"
MP	25		
MI	25	⋆⋆	·
SP	25		
SI	24	⋆	

Figure 3: ICM interface after clicking "Colleges and Universities".

Figure 4: ICM-US interface after clicking "Colleges and Universities".

Interface Card Model (ICM): Summary

- A very general model for optimizing any interactive system
- Enables using an algorithm to compute an optimal interface (i.e., "interface computing")
- When modeling interactive IR, it can be regarded as a special case of the IR game framework by defining an action as an interface card
- Interesting analytical conclusions (e.g., balanced tag selection, benefit of having a search box available for a user most of the time)
- Derivation of a useful algorithm for optimizing simple navigation card interfaces adaptive to both display size and user feedback
- Covers IIR Prob. Ranking Principle (IIR-PRP) as a special case

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Theoretical Justification for Ranking

- **Probability Ranking Principle** [Robertson 77]: Returning a ranked list of documents in descending order of probability that a document is relevant to the query is the optimal strategy under the following two assumptions:
  - The utility of a document (to a user) is **independent** of the utility of any other document
  - A user would browse the results **sequentially**
- Do these two assumptions hold? No!

S.E. Robertson, The probability ranking principle in IR. *Journal of Documentation* **33**, 294-304, 1977
http://staff.city.ac.uk/~sb317/papers/ProbabilityRankingPrinciple.pdf

IIR-Probability Ranking Principle (IIR-PRP) [Fuhr 08]

- Does *not* assume independence of relevance (but still assuming sequential browsing, which is further relaxed in Interface Card Model)
- Main idea
  - Acknowledges user's interest may change due to interaction, e.g. after reading a relevant document
  - Generalizes in the context of interaction:
    - Documents => binary choices
    - Relevance => rewards
    - Number of documents to scan through => costs
  - System presents list of choices to user; user evaluates choices in linear order; only positive decisions/choices are of benefit to a user

Norbert Fuhr. 2008. A probability ranking principle for interactive information retrieval. *Inf. Retr.* 11, 3 (June 2008), 251-265. DOI=http://dx.doi.org/10.1007/s10791-008-9045-0

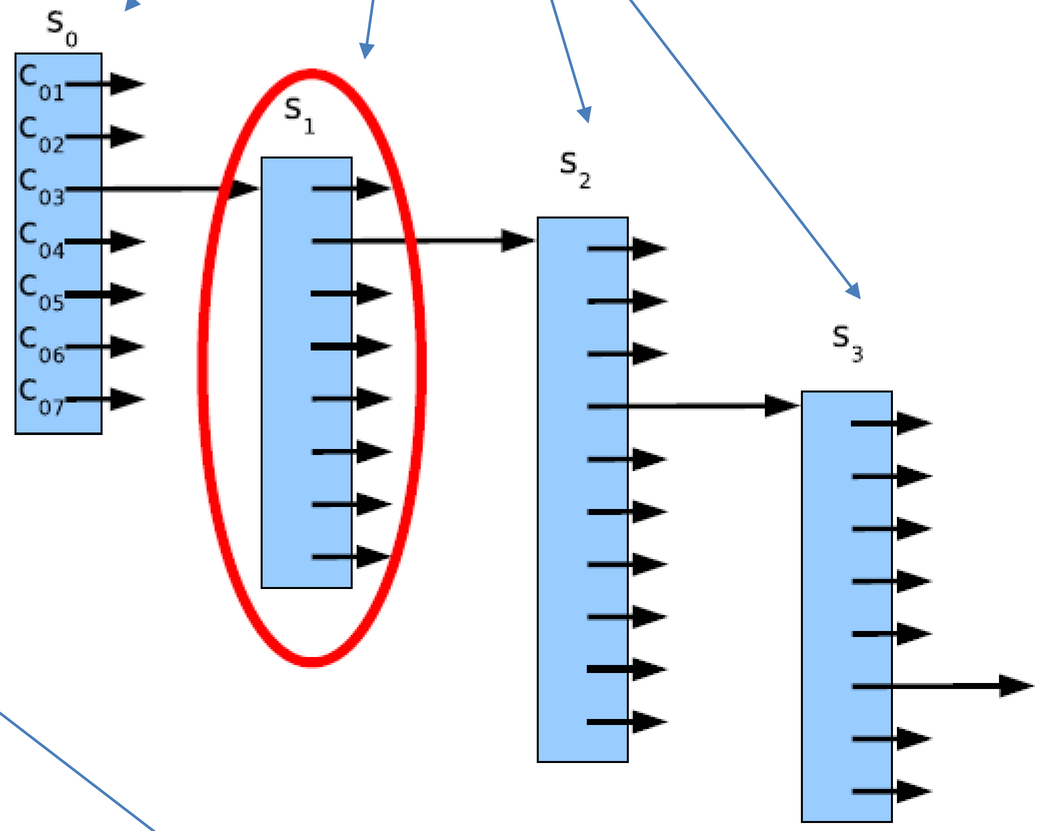
Generality: Many Examples of Decision Lists

- Ranked list of documents
- List of summaries
- List of document cluster
- KWIC list
- List of expansion terms
- Links to related documents
- …

Modeling Binary Decision in a Single Situation

Situations

Binary Choice C_{03} has been **accepted**, leading to **Situation s_1**



Expected Benefit of Choice C_{ij}

$$E(C_{ij})=e_{ij}+p_{ij}a_{ij}$$

e_{ij}: examination cost (negative benefit)

p_{ij}: prob. of accepting

a_{ij}: (positive) benefit of accepting

Example for Expected Benefit

After formulating a query, a user may choose to perform the following actions with the corresponding parameter triple (e_{ij}, p_{ij}, b_{ij})

1. $(-1.0, 0.3, 8)$ add expansion term to the query
2. $(-2.0, 0.4, 10)$ look at the first result list entry
3. $(-10.0, 0.4, 25)$ immediately go to the first document
4. $(-5.0, 0.3, 20)$ look at an aggregated summary of the top ranking documents

In which order should these choices be presented to the user?

1. $(-1.0 + 0.3 \cdot 8) = 1.4$
2. $(-2.0 + 0.4 \cdot 10) = 2$
3. $(-10.0 + 0.4 \cdot 25) = 0$
4. $(-5.0 + 0.3 \cdot 20) = 1$

Slide credit: Norbert Fuhr

Optimization of the Ranking of a List of Choices

- Expected benefit of a list of choices: $r_i =< c_{i1}, c_{i2}, \ldots, c_{i,n_i} >$

$$\begin{aligned} E(r_i) &= e_{i1} + p_{i1}a_{i1} + \\ & (1-p_{i1})\left(e_{i2} + p_{i2}a_{i2} + \right. \\ & (1-p_{i2})\left(e_{i3} + p_{i3}a_{i3} + \right. \\ & \ldots \\ & \left.\left.(1-p_{i,n-1})\left(e_{in} + p_{in}a_{in}\right)\ \right)\right) \\ &= \sum_{j=1}^{n}\left(\prod_{k=1}^{j-1}(1-p_{ik})\right)\left(e_{ij} + p_{ij}a_{ij}\right) \end{aligned}$$

Prefer high relevance

Prefer low exam. cost

- Solution: Ranking in descending order of $\varrho(c_{ij}) = a_{il} + \frac{e_{il}}{p_{il}}$

Prefer high prob. of acceptance

IIR-PRP as a special case of Interface Card Model

$$E(u^t|c^t,q^t) = \sum_{a^{t+1}\in\mathcal{A}(q^t)} p(a^{t+1}|c^t,q^t)\,u(a^{t+1}|c^t,q^t)$$

$$q^t = e^t \qquad \mathcal{A}(e^t) = \{a_0^{t+1}, a_1^{t+1}\}$$

$$p(e^t) = p(a_0^{t+1}|e^t) = 1 - p(a_1^{t+1}|e^t)$$

$$r(e^t) = r(a_0^{t+1}|e^t) \qquad r(a_1^{t+1}|e^t) = E(u^{t+1}|e^{t+1})$$

$$s(a_0^{t+1}|e^t) = s(a_1^{t+1}|e^t) = s(e^t)$$

$$E(u^t|e^t) = -s(e^t)+p(e^t)r(e^t)+(1-p(e^t))E(u^{t+1}|e^{t+1})$$

High utility

Low examination cost

$$\rho(e^t) \stackrel{\text{def}}{=} r(e^t) - \frac{s(e^t)}{p(e^t)}$$

High probability of acceptance by user

IIR-PRP

$$E(u^1|\mathbf{e}) = \sum_{t=1}^{\infty} \left(\prod_{j=1}^{t-1} (1 - p(e^j)) \right) (-s(e^t) + p(e^t)\, r(e^t))$$

$$E(u^t|e^t) = -s(e^t) + p(e^t) r(e^t) + (1 - p(e^t)) E(u^{t+1}|e^{t+1})$$

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Applying Economics to IIR: Model User Decisions

ICM

$$\underset{q^t}{\text{maximize}} \quad E(u^t|c^t, q^t)$$

$$= \sum_{a^{t+1} \in \mathcal{A}(q^t)} \underline{p(a^{t+1}|c^t, q^t)}\, u(a^{t+1}|c^t, q^t)$$

$$\text{subject to} \quad f_c^t(q^t) \leq 0$$

How can we accurately model a user's decision on choosing an action?

p(action|context, interface) =?

Which action to take ≈ Which product to buy ?

Azzopardi, L., & Zuccon, G. (2018). Economics models of interaction: a tutorial on modeling interaction using economics. In A. Oulasvirta, P. O. Kristensson, X. Bi, & A. Howes (Eds.), *Computational Interaction* Oxford.

Economics Model of User Interaction

- Main assumptions
  - A user makes a sequence of decisions during interaction (same assumption as in ICM or IIR-PRP)
  - A user chooses an action to maximize the expected utility (e.g., gain of useful information) while minimizing the cost (e.g., time spent and/or cognitive load) ➔ Similar to decision models in Economics
  - A user gains experience while using a system and is rational
- Goal: develop formal models of user's decision behavior, i.e., modeling **p(action|context, interface) in the ICM**
- So far, the main achievement is a formal description of relations between decision factors and decision outcomes at the level of observable variables (no latent variables), mostly simplified parametric models

Building an Economics Model

[Varian 16, Azzopardi & Zuccon 18]

- Describe the problem context
- Specify the functional relationships between the interactions and the cost and benet of those interactions,
- Solve the model,
- Use the model to generate hypotheses about behaviours,
- Compare the predictions with observations in the literature and/or experimental data, and,
- Refine and revise the theory accordingly, and iterate the procedure.

Varian, H. R. How to build an economic model in your spare time. The American Economist 61, 1 (2016), 81{90.

A Sample Economics Model [Azzopardi, L., & Zuccon 18]

- Model of optimal query length: query length= W
  - Benefit: $b(W)=k*\log_a(W+1)$: k (search result quality), a (decaying factor)
  - Cost: $c(W) = W*c_W$: c_W (cost per word)
  - Profit: $b(W)-c(W)=k*\log_a(W+1)- W*c_W$
  - Solve for maximizing profit ➔ $W^* = \frac{k}{c_w \cdot \log a} - 1$
- Model provides interesting testable hypotheses (e.g., queries are likely to be longer when using query auto-completion than without due to the reduced cost.
- However, the parametric forms of the model are often overly simplified (assumptions do not hold)

Additional Economics Models [Azzopardi, L., & Zuccon 18]

- Model of Assessment Depth (how far down the list a user would go)
- Model of querying (should a user issue a query?)
- Testable hypotheses have been derived from the models
- Overall, promising new direction, but so far the testable hypotheses seem to be either obvious or superficial relations between observable variables
- A necessary initial step toward formally specifying the user model in the IR Game framework or the user action model in ICM

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A Theoretical Framework for Conversational Search

[Radlinski & Craswell 17]

- Attempted to formalize conversational search, i.e., define the space of user actions and system responses (i.e., “moves”) in an IR game
- Proposed a set of properties to measure “conversational”
- Showed that the framework is general enough to cover many specific application scenarios

Filip Radlinski and Nick Craswell. 2017. A Theoretical Framework for Conversational Search. In *Proceedings of the 2017 Conference on Conference Human Information Interaction and Retrieval* (CHIIR '17). ACM, New York, NY, USA, 117-126. DOI: https://doi.org/10.1145/3020165.3020183

Space of User Actions and System Responses

[Radlinski & Craswell 17]

System Provides →

Feedback Accepted ↓

Feedback Accepted	Nothing	Partial Item field (F) / field+value (F+V) / cluster (C)	Complete Item
Pref/Rating		F: n/a F+V: Choice/confirmation C: Hierarchical search	Recommendation
Critique		F: Fielded Search F+V: Unit Critiques C: n/a	Item Critiques
Free Text	Search box	F: Slot filling F+V: n/a C: n/a	

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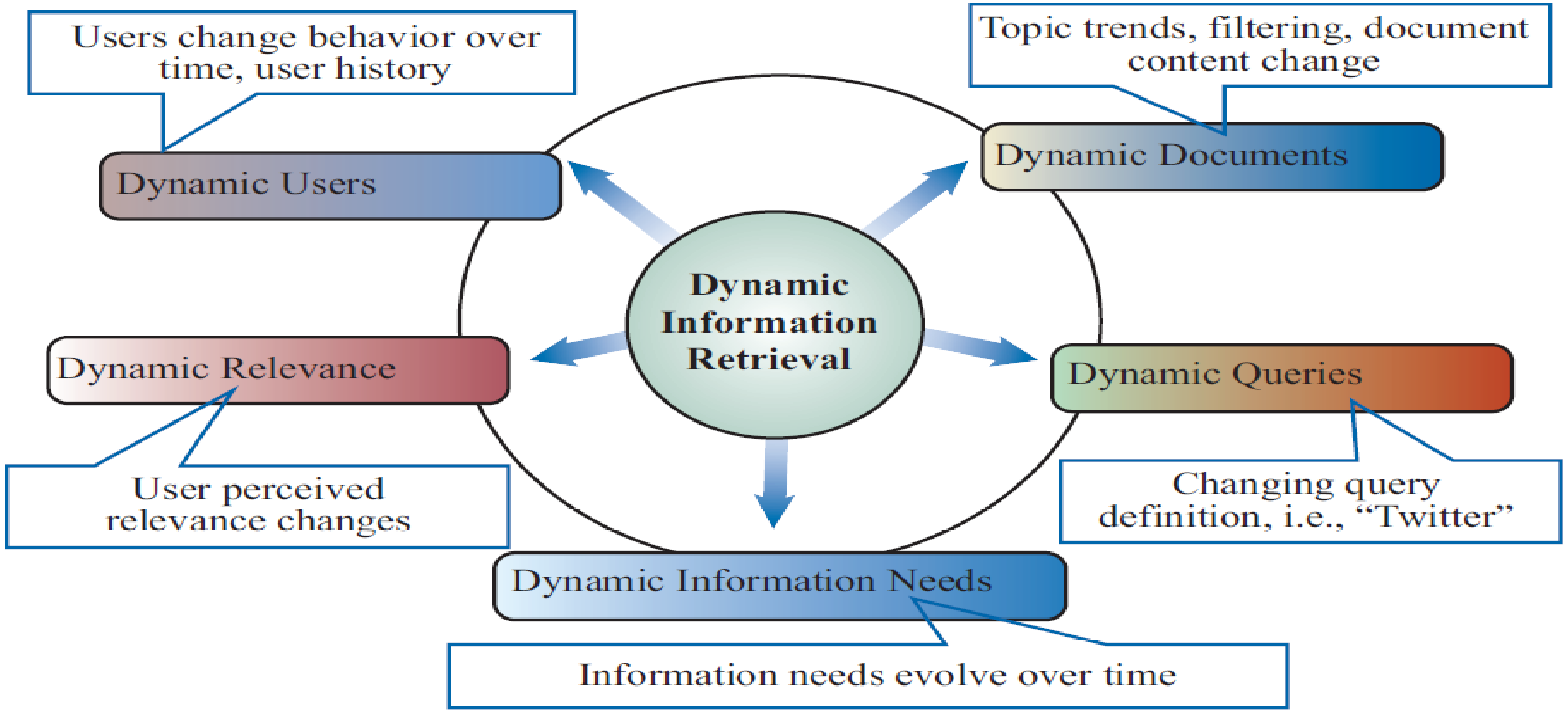
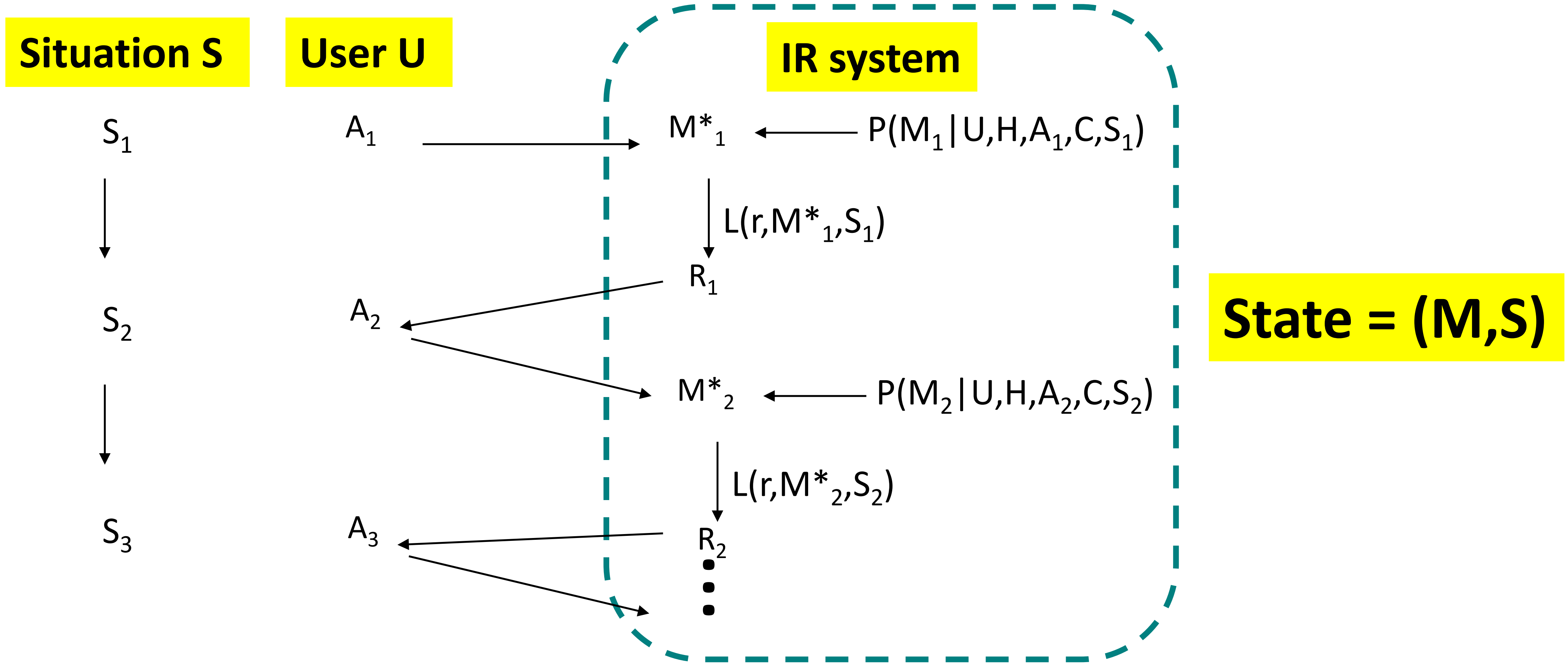
Dynamic Information Retrieval [Yang et al. 16]



Dynamics ➔ Updating Situation S and User Model M in the IR Game framework

Grace Hui Yang, Marc Sloan, and Jun Wang. 2016. *Dynamic Information Retrieval Modeling*. Morgan & Claypool Publishers.

Dynamic IR = Dynamic State (M,S)



Can be modeled by a Partially Observable Markov Decision Process:
POMDP, Multi-armed Bandit, Belief POMDP, …
Optimal Policy Computation: Reinforcement Learning

Major Work in Dynamic IR

- Distinctive feature: optimization of sequential decisions = optimization of expected utility over a horizon of future interactions
- Tasks
  - Session Search: Optimization of the overall results in a session (e.g., [Guan et al. 13], [Luo et al. 14])
  - Multipage Search: Optimization of multiple-page search results (e.g., [Jin et al. 13])
  - Online learning to rank: Search engine as learning agent (e.g., [Hofmann et al. 11], [Hofmann 13])
- Techniques
  - MDP/POMDP, Reinforcement Learning, Multi-armed Bandit

Modeling Interactions in Session Search [Yang et al. 16]

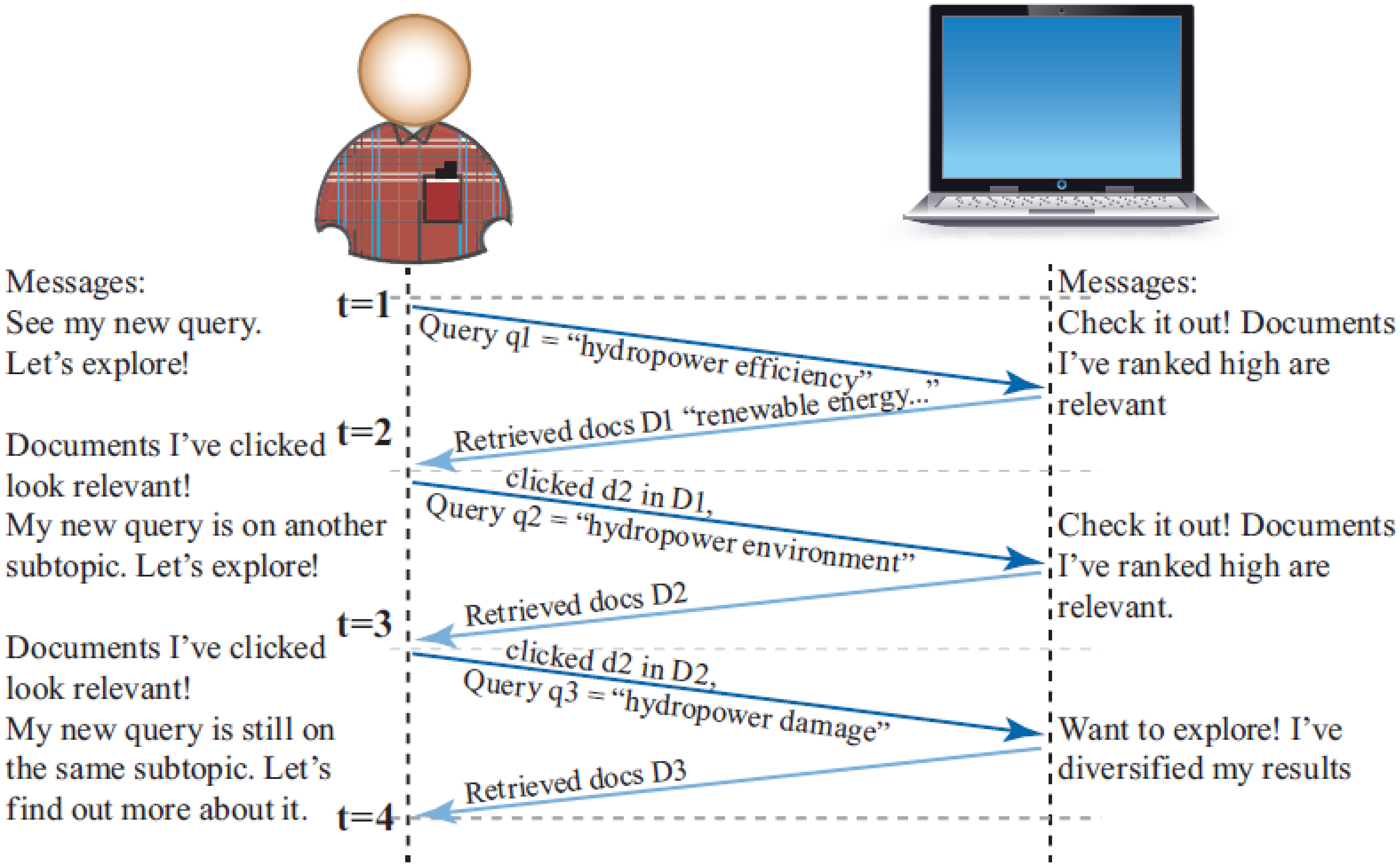
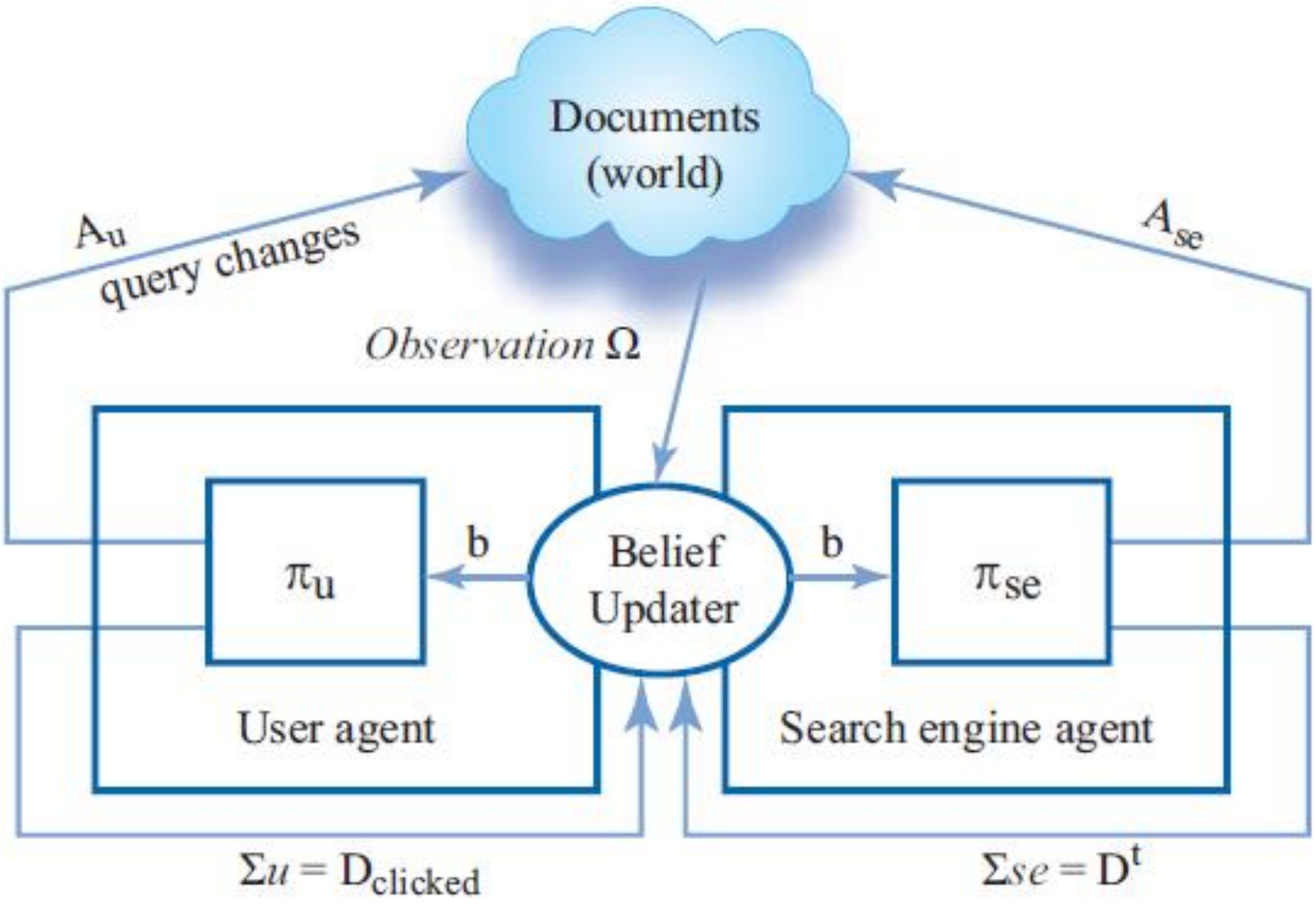


Figure 4.3: Interactions in session search. (Example is from TREC'14 Session 52. d_n is the n^{th} document in a ranked list D at iteration t.)

Session Search as a Dual-Agent Stochastic Game (DASG)



Two New Ideas in the DASG Model

- 1. Joint modeling of the decision processes of both users and search engines, capturing duality of user and system decision making
- 2. Explicitly modeling communications between a user and a search engine
- Facilitating optimization of human-machine collaboration, communication, and cognition

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Instantiation of IR Game

- **Situation S**: can include time, location, and other environmental factors that are relevant to a task
- **Document Collection C:** naturally available in any application
- **User U**: can include any information we know about a user (or group)
- **User interaction history H:** naturally accumulated over time
- **User Actions** and **System Responses R(A)**: all interfaces (moves of the game)
- **Loss Function L(R,M,S):** captures the objective of the game
- **User Model M**: can include everything that we can infer about a user relevant to deciding how to respond to a user's action
- **Inference of User Model P(M|U, H, At, C,S):** capture system's belief about user model M

General framework for developing novel IIR strategies

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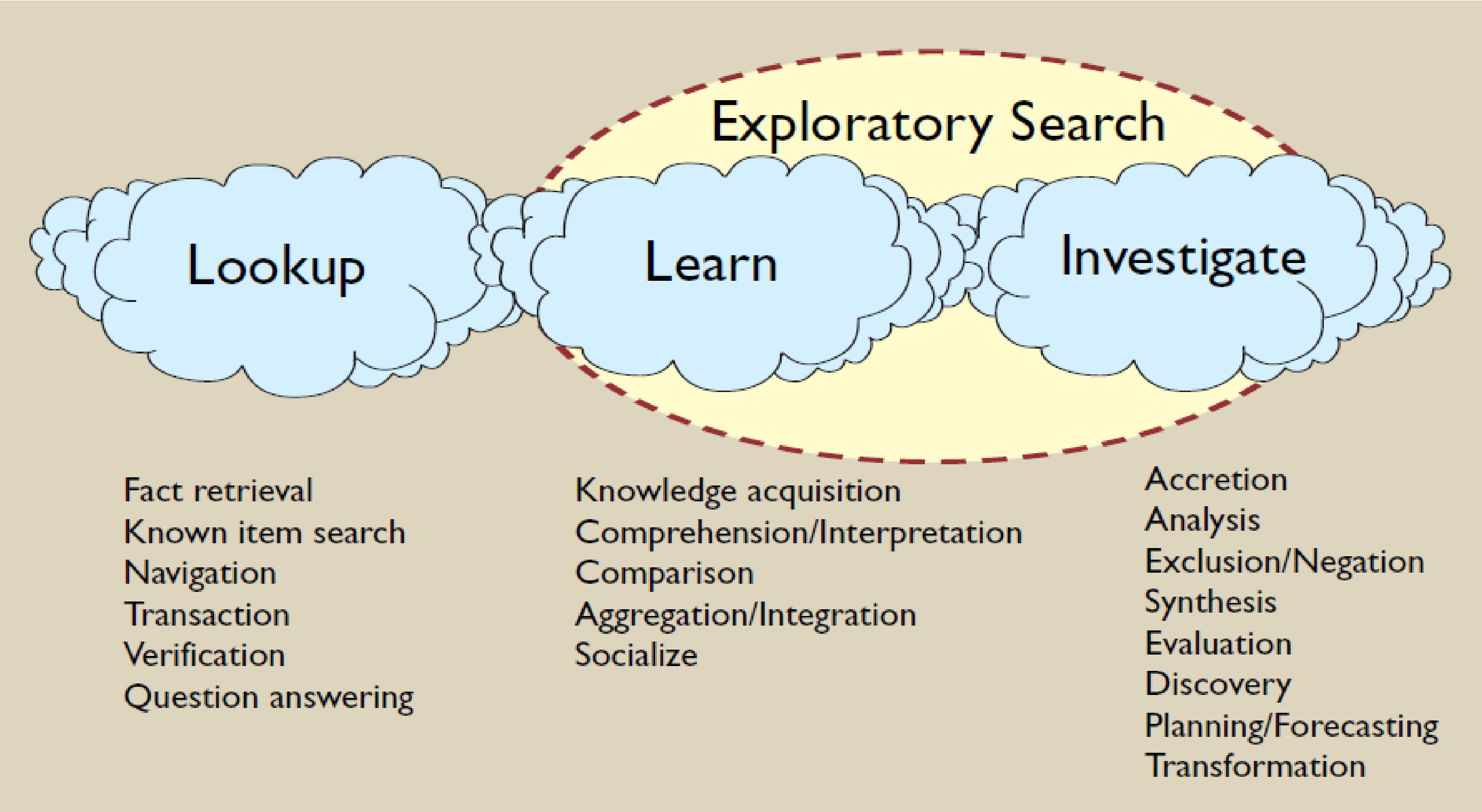
Marchionini's Typology of Search Tasks [Marchionini 06]



How can we design a general IIR system to support all these tasks?

Gary Marchionini. 2006. Exploratory search: from finding to understanding. *Commun. ACM* 49, 4 (April 2006), 41-46. DOI: https://doi.org/10.1145/1121949.1121979

Taxonomy of Web and E-com Search

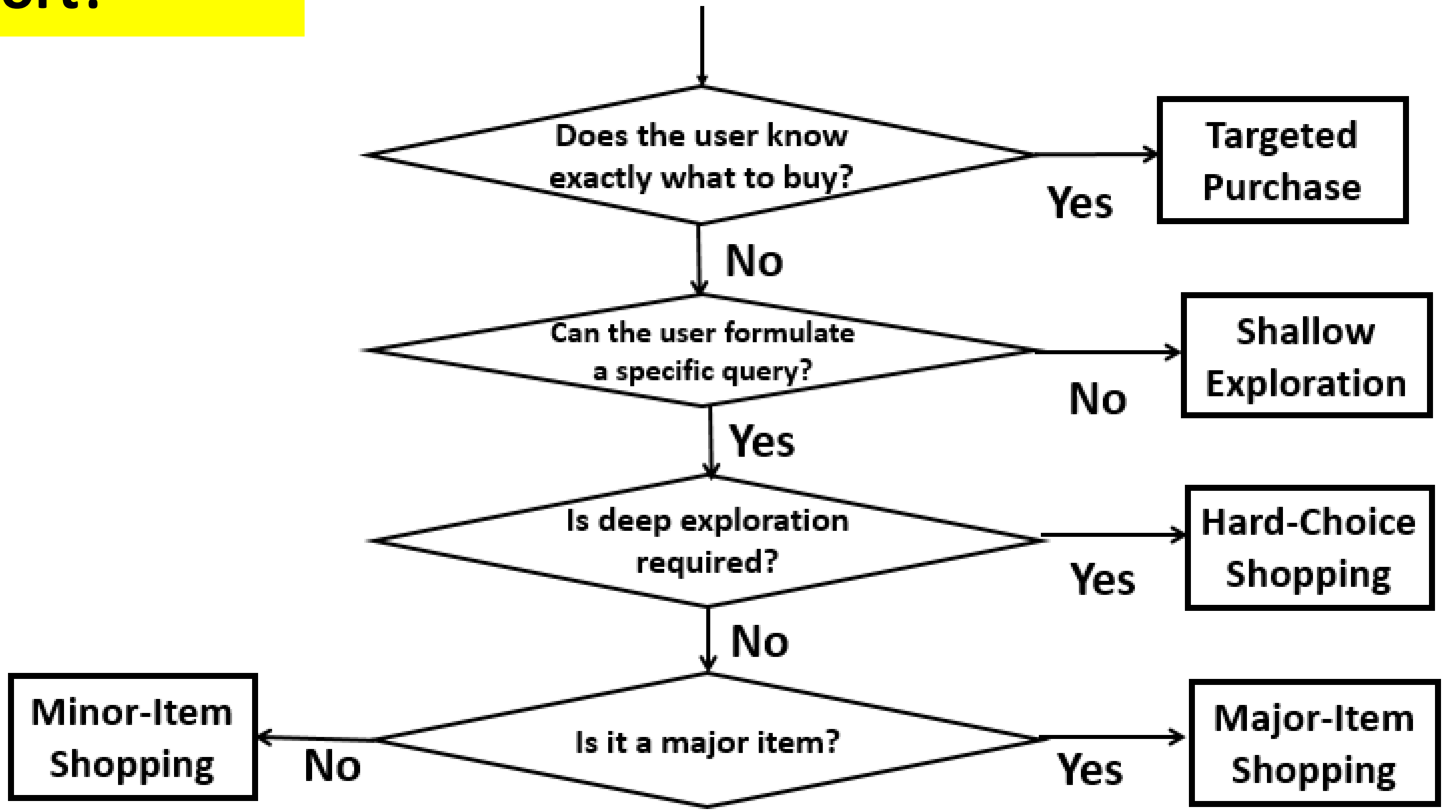
How can we model a user's task and provide task support?

Web Search [Broder 02]

- **Navigational**
- **Informational**
- **Transactional**

Andrei Broder. A taxonomy of web search. SIGIR Forum, 36(2):3–10, 2002.

E-Com Search [Sondhi et al. 18]

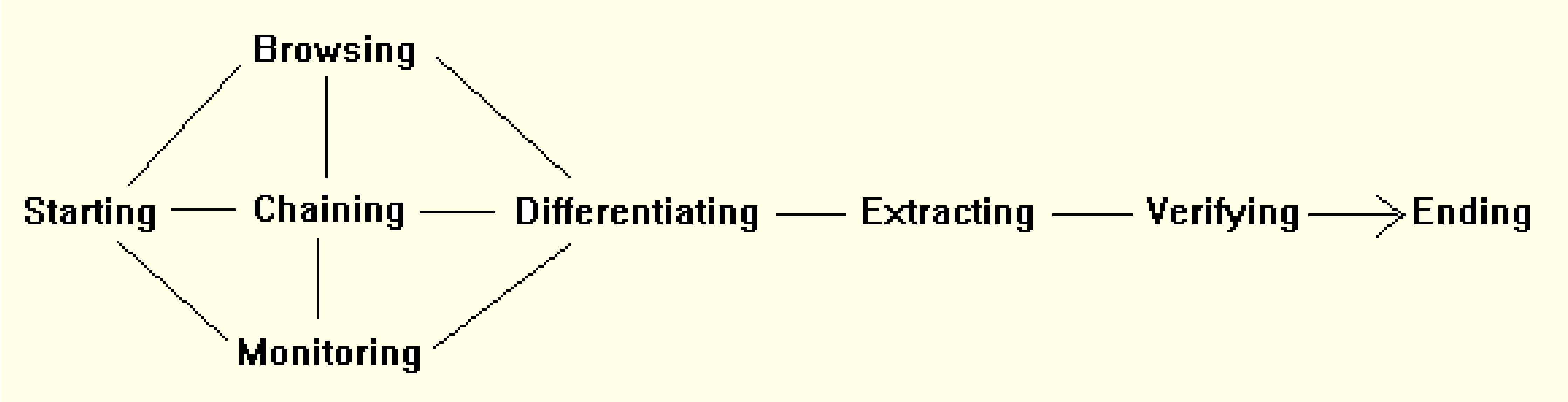


Parikshit Sondhi, Mohit Sharma, Pranam Kolari, ChengXiang Zhai: A Taxonomy of Queries for E-commerce Search. SIGIR 2018: 1245-1248

Conceptual Models for Exploratory Information Seeking

- Ellis' behavioral model [Ellis 89]:
  - Based on empirical study of information seeking patterns of academic social scientists
  - 6 categories: Browsing, Chaining, Monitoring, Differentiating, Extracting, and Verifying
- Meho & Tibbo's extension of Ellis' model [Meho & Tibbo 03]
  - Added 3 additional categories: Accessing, Networking, Information Managing

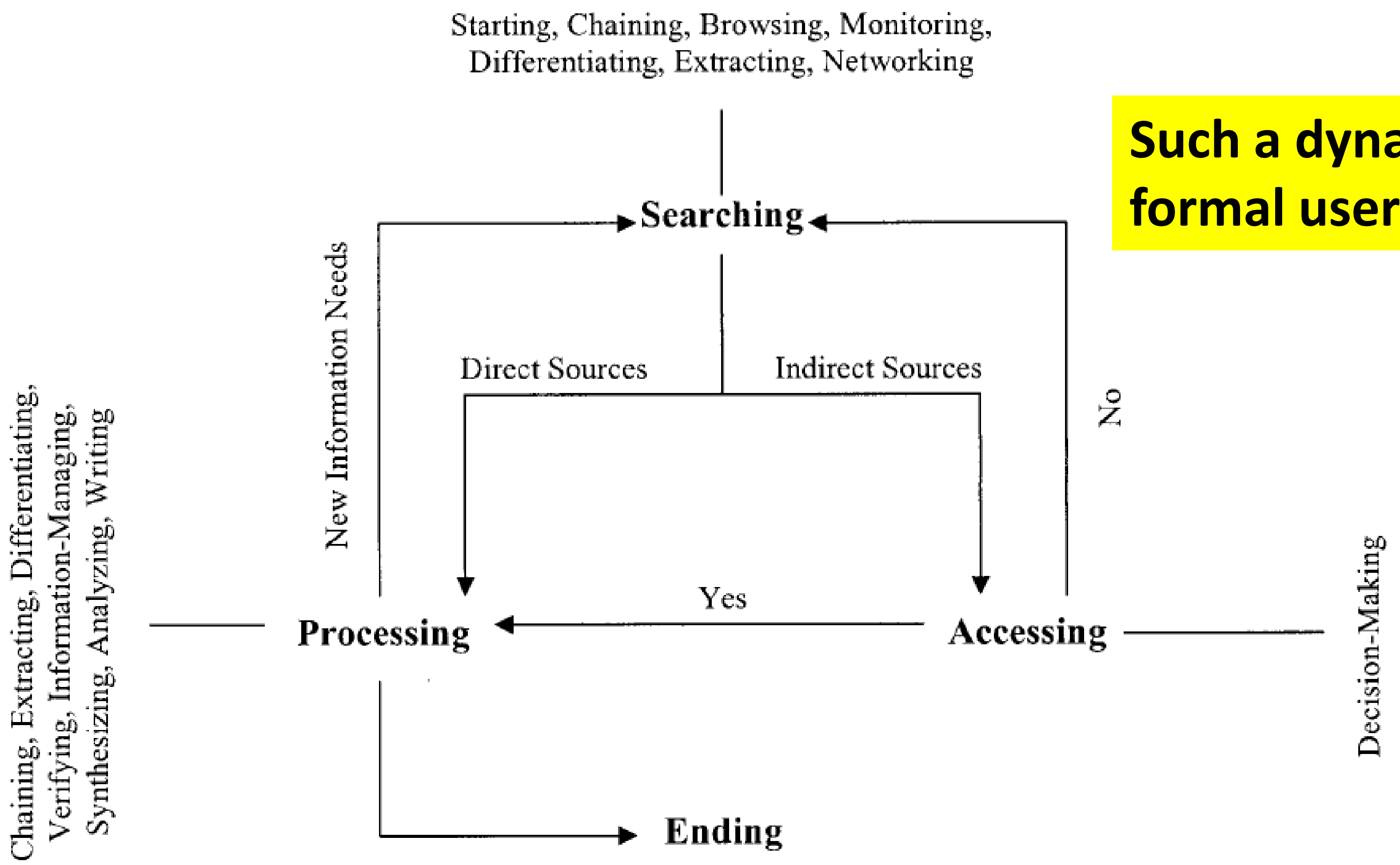
Ellis' Behavioral Model of Information Seeking



How can such a model inform the design of interface cards and user actions?

D. Ellis. A behavioural approach to information retrieval system design. Journal of Documentation, 45(3):171–212, 1989.

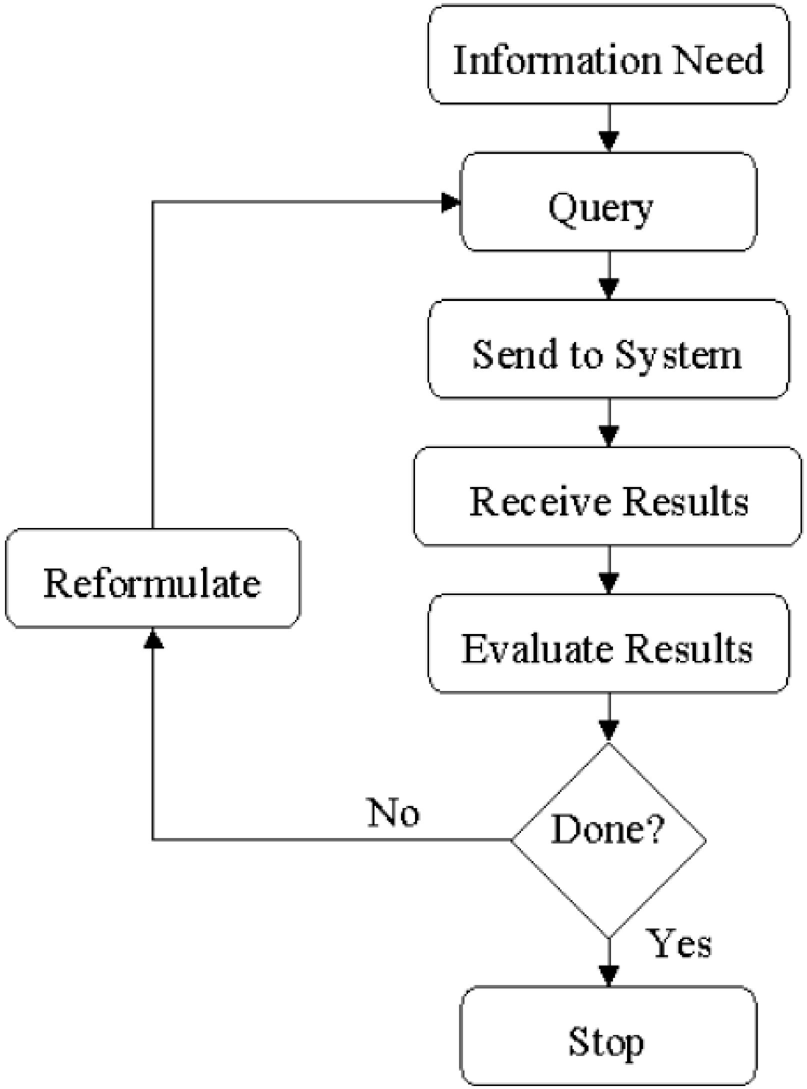
Meho & Tibbo's extension of Ellis' model



Such a dynamic model suggests a formal user/task model based on MDP

Lokman I. Meho and Helen R. Tibbo. Modeling the information-seeking behavior of social scientists: Ellis's study revisited. Journal of the American Society for Information Science and Technology, 54(6): 570–587, 2003.

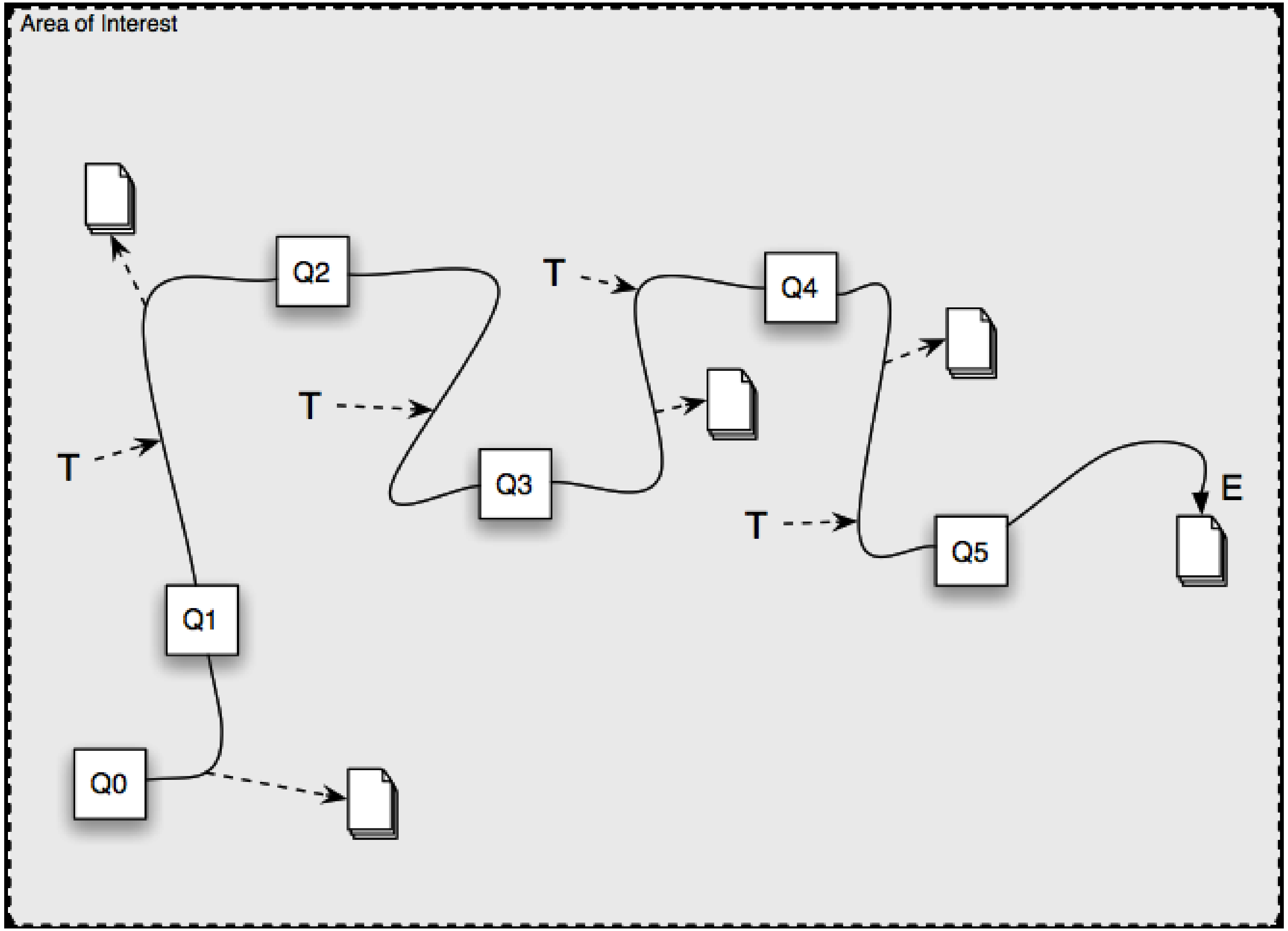
Basic Model for Search Process



This simple model (the simplest IR game) is the common "backbone" of all existing search engine systems

Lots of room to further optimize…

Berry Picking Model [Bates 89]



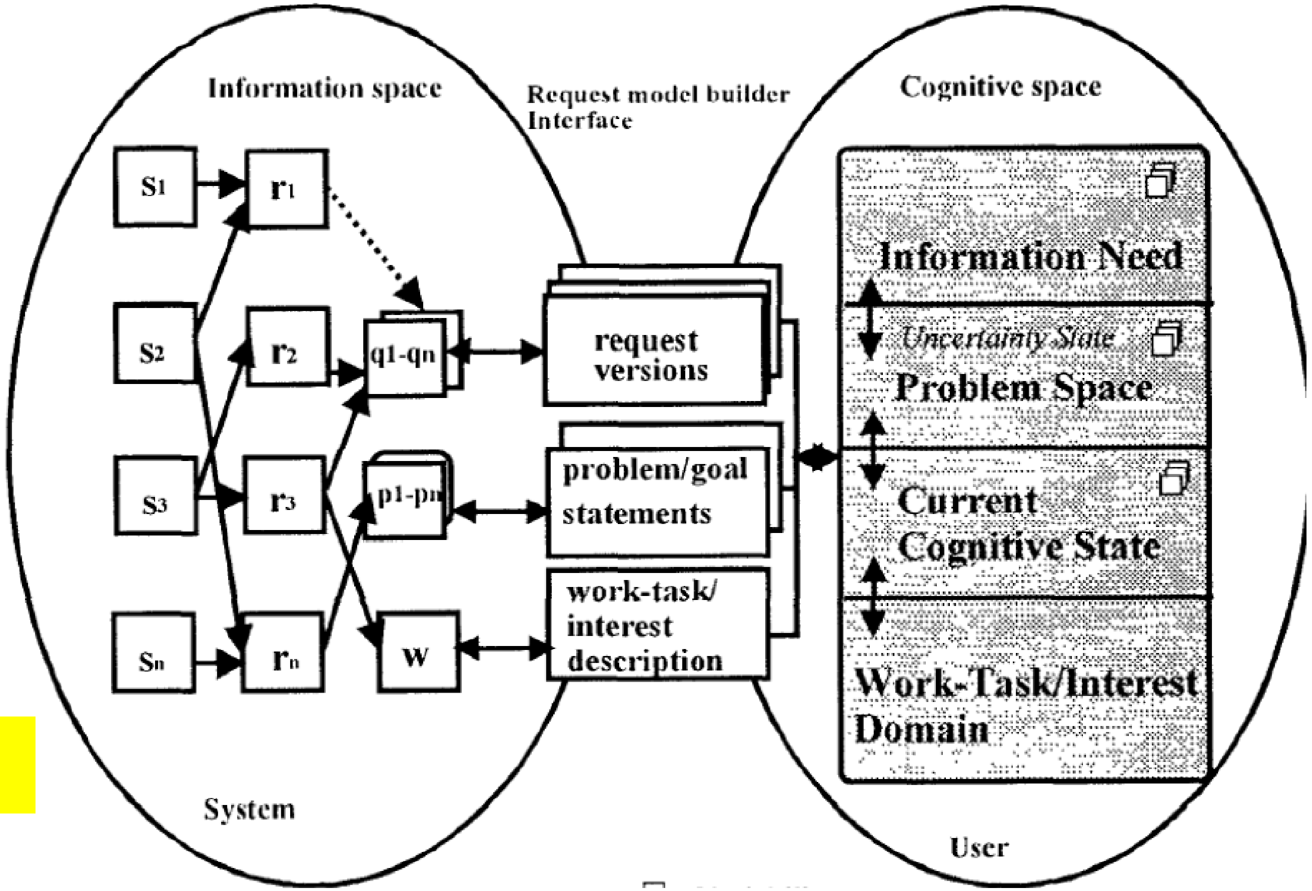
Suggests the need for system to support storing history and accumulating information

Belkin's ASK and Ingwersen's Cognitive IR model

ASK =
Anomalous State of Knowledge

Information Need ➔ ASK
➔ User can't describe accurately the need, thus needs to learn during search

How can a system support learning?



N. J. Belkin. Anomalous states of knowledge as a basis for information retrieval. Canadian Journal of Information Science, 5:133–143, May 1980.

P. Ingwersen. Polyrepresentation of information needs and semantic entities, elements of a cognitive theory for information retrieval interaction. ACM SIGIR 1994.

Conceptual Models and Design of IIR Systems

- Conceptual models provide a "roadmap" for designing IIR systems
- IIR systems inevitably vary according to the task to be supported
- The existing conceptual models are all high level and only cover some tasks
  - Need to refine the current models to actually impact the design of an IIR system = Using conceptual models to design interface cards and user actions ("top down," theory-driven)
  - Need to develop new conceptual models based on formal IIR models ("bottom up," application-driven)

Basic Search Model: Techniques & Algorithms

- Interactive query formulation and refinement
- Feedback
- Diversification of search results
- Whole session/page optimization

Outline

- Background
- Formal Models for IIR
- Techniques and Algorithms for IIR
  - Conceptual Models for Information Seeking and retrieval
  - $\boxed{\text{Interactive Query Formulation and Refinement}}$
  - Feedback
  - Diversification of results
  - Whole session/page optimization
- Evaluation of IIR
- Summary

Interactive Query Formulation and Refinement

- Different notions of a query
  - Query = keywords
  - Query = information need description
  - Query = task specification
  - Query can have many constraints and preferences in other dimensions
- Query formulation can be supported in many different ways on an interface (see Marti Hearst's book on Search User Interface)
- How can a system minimize a user's effort on query formulation?
  - Query auto-completion (e.g., [Bast & Weber 06])
  - Query suggestion (e.g., [Jones et al. 06])
  - Interactive query expansion (e.g., [Kuzi et al. 19])
  - Query clarification (sense disambiguation) (e.g., [Kotov & Zhai 11])

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Feedback

- Relevance feedback: User judges search results explicitly
- Implicit feedback: Infer relevance judgments based on user's clickthroughs
- Many interesting new opportunities are possible
  - Explanatory feedback (documents like this, but also matching "X"; documents like this except for not matching "Y", …)
  - In general, it's beneficial to include more options on an interface card so as to enable users to give more informative feedback to the system and do that at any time of interaction
  - Active learning → Active feedback (presenting results so as to maximize benefit of learning from a user's interaction)

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IR Game & Diversification: 3 Different Reasons for Diversification

1. Redundancy reduction → reduce user effort

2. Diverse information needs (e.g., overview, subtopic retrieval) → increase the immediate utility

3. Active relevance feedback → increase future utility

Capturing diversification with different loss functions

1. **Redundancy reduction**: Loss function includes a redundancy measure
   – Special case: list presentation + MMR [Zhai et al. 03]
2. **Diverse information needs**: loss function defined on latent topics
   – Special case: PLSA/LDA + topic retrieval [Zhai 02]
3. **Active relevance feedback**: loss function considers both relevance and benefit for feedback (online learning to rank, dynamic IR)
   – Special case: hard queries + feedback only [Shen & Zhai 05]

Diversify = Remove Redundancy (e.g., [Zhai et al. 03])

$$\pi^* = \arg\min_{\pi} \int_{\Theta} L(\pi,\theta)\, p(\theta \mid q,U,C,\vec{S})\, d\theta = \arg\min_{\pi} \sum_{j=1}^{N} \left(\sum_{i=j}^{N} s_i \right) r(d_{\pi_j} \mid d_{\pi_1},\ldots,d_{\pi_{j-1}})$$

$$r(d_k \mid d_1,\ldots,d_{k-1}) = \int_{\Theta} l(d_k \mid d_1,\ldots,d_{k-1},\theta)\, p(\theta \mid q,U,C,\vec{S})\, d\theta$$

Greedy Algorithm for Ranking: Maximal Marginal Relevance (MMR)

$$l(d_k \mid d_1,\ldots,d_{k-1},\theta_Q,\{\theta_i\}_{i=1}^{k-1}) = c_2\, p(R=1 \mid d_k)(1-p(New \mid d_k)) + c_3(1-p(R=1 \mid d_k))$$

Cost	NEW	NOT-NEW
REL	0	C2
NON-REL	C3	C3

$$\overset{Rank}{=} p(R=1 \mid d_k)(1-\rho-p(New \mid d_k))$$

$$\overset{Rank}{\approx} p(q \mid d_k)(1-\rho-p(New \mid d_k))$$

"Willingness to tolerate redundancy"

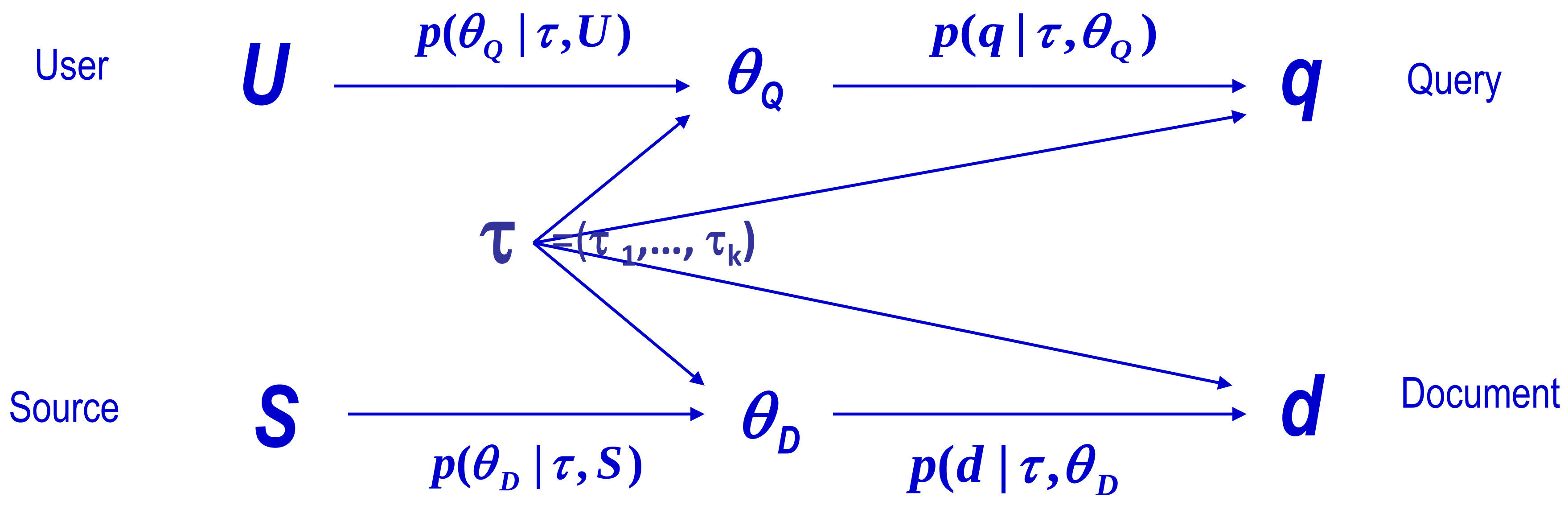
$$where,\ \ \rho = \frac{c_3}{c_2} > 1$$

C2<C3, since a redundant relevant doc is better than a non-relevant doc

Diversity = Satisfy Diverse Info. Need
(e.g. , [Zhai 02], [Jiang et al,. 17])

- Need to directly model latent aspects and then optimize results based on aspect/topic matching
- Reducing redundancy doesn’t ensure complete coverage of diverse aspects

Aspect Generative Model of Document & Query [Zhai 02]



PLSI: $$p(d \mid \tau,\theta_D) = \prod_{i=1}^{n} \sum_{a=1}^{A} p(d_i \mid \tau_a) p(a \mid \theta_D) \quad where,\ d = d_1 \ldots d_n$$

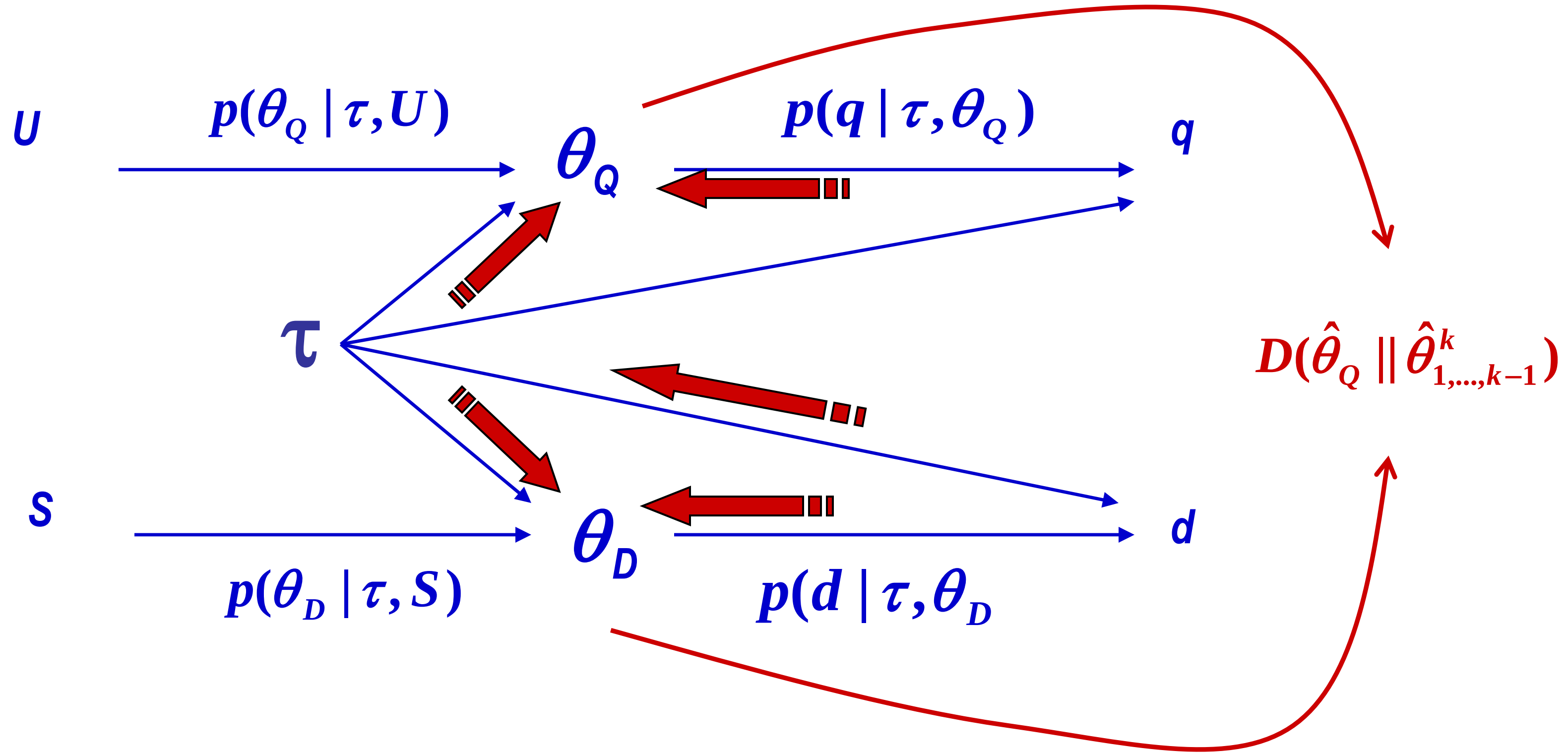
LDA: $$p(d \mid \tau,\alpha) = \int_{\Theta} \prod_{i=1}^{n} \sum_{a=1}^{A} p(d_i \mid \tau_a) p(a \mid \theta) Dir(\theta \mid \alpha) d\theta$$

Aspect Loss Function [Zhai 02]

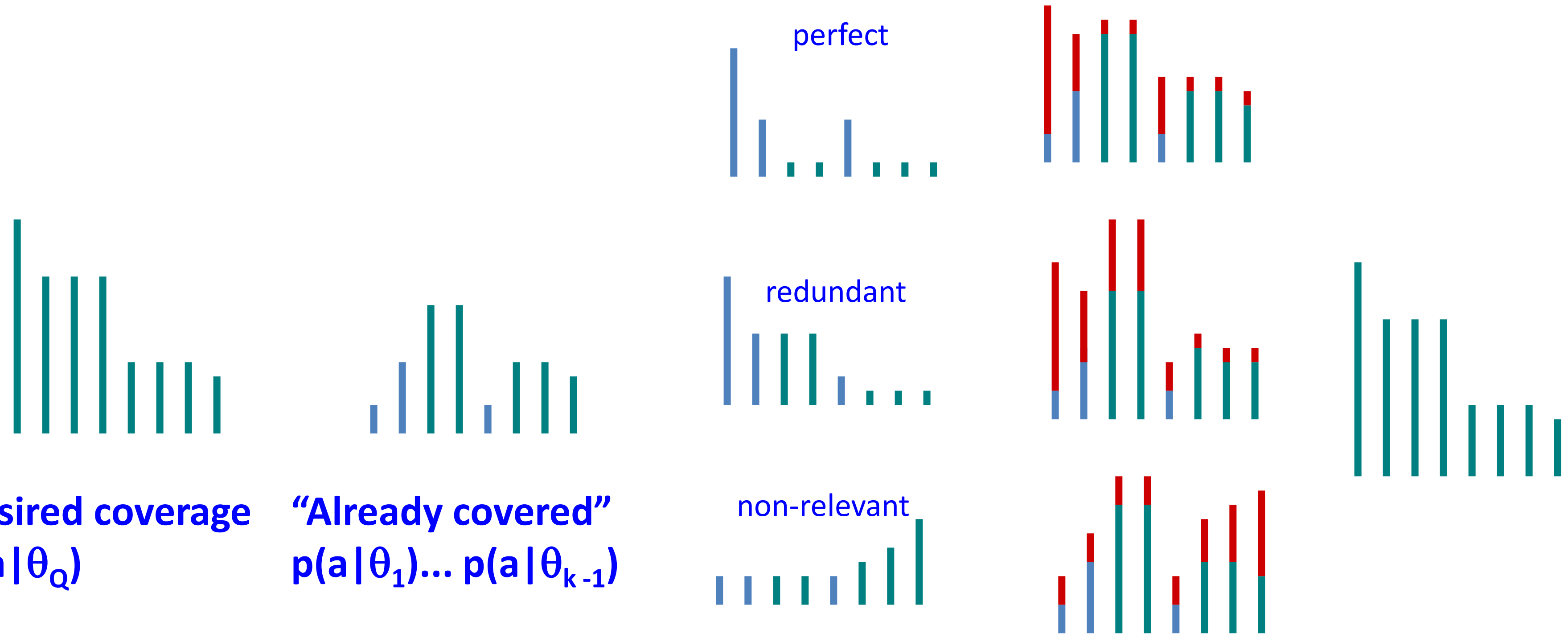
$$l(d_k \mid d_1,\ldots,d_{k-1},\theta_Q,\{\theta_i\}_{i=1}^{k-1}) = D(\theta_Q \,\|\, \theta_{1,\ldots,k-1}^k)$$

where,

$$p(a \mid \theta_{1,\ldots,k-1}^k) = \frac{\mu}{k-1}\sum_{i=1}^{k-1} p(a \mid \theta_i) + (1-\mu)\,p(a \mid \theta_k)$$



Aspect Loss Function: Illustration



Desired coverage
$p(a|\theta_Q)$

"Already covered"
$p(a|\theta_1)$... $p(a|\theta_{k-1})$

New candidate
$p(a|\theta_k)$

Combined coverage
$p(a|\theta_k)$

Diversify = Active Feedback [Shen & Zhai 05]

Decision problem: Exploration-Exploitation Tradeoff

Decide subset of documents for relevance judgment

$$D^* = \arg\min_D \int_\Theta L(D,\theta)\, p(\theta \mid U, q, C)\, d\theta$$

$$L(D,\theta) = \sum_{\vec{j}} l(D, \vec{j}, \theta)\, p(\vec{j} \mid D, \theta, U)$$

$$= \sum_{\vec{j}} l(D, \vec{j}, \theta) \prod_{i=1}^{k} p(j_i \mid d_i, \theta, U)$$

Independent Loss

$$L(D,\theta) = \sum_{\vec{j}} l(D, \vec{j}, \theta) \prod_{i=1}^{k} p(j_i \mid d_i, \theta, U)$$

Independent Loss

$$l(D, \vec{j}, \theta) = \sum_{i=1}^{k} l(d_i, j_i, \theta)$$

$$L(D,\theta) = \sum_{i=1}^{k} \sum_{\vec{j}} l(d_i, j_i, \theta) \prod_{i=1}^{k} p(j_i \mid d_i, \theta, U)$$

$$D^* = \arg\min_{D} \sum_{i=1}^{k} \sum_{j_i} \int_{\Theta} l(d_i, j_i, \theta) p(j_i \mid d_i, \theta, U) p(\theta \mid U, q, C) d\theta$$

$$r(d_i) \equiv \sum_{j_i} \int_{\Theta} l(d_i, j_i, \theta) p(j_i \mid d_i, \theta, U) p(\theta \mid U, q, C) d\theta$$

Independent Loss (cont.)

$$r(d_i) = \sum_{j_i} \int_\Theta l(d_i, j_i, \theta) p(j_i \mid d_i, \theta, U) p(\theta \mid U, q, C) d\theta$$

$$\forall d_i \in C, \quad l(d_i, 1, \theta) = C_1,$$
$$l(d_{i,} 0, \theta) = C_0, \; C_1 < C_0$$

$$l(d_i, 1, \theta) = \log p(R = 1 \mid d_i, \theta) \quad \forall d_i \in C$$
$$l(d_i, 0, \theta) = \log p(R = 0 \mid d_i, \theta) \quad \forall d_i \in C$$

$$r(d_i) = C_0 + (C_1 - C_0) \int_\Theta p(j_i = 1 \mid d_i, \theta, U) p(\theta \mid U, q, C) d\theta$$

Top K

$$r(d_i) = -\int_\Theta H(R \mid d_i, \theta) p(\theta \mid U, q, C) d\theta$$

Uncertainty Sampling

Dependent Loss

$$L(D,U,\theta) \approx -\sum_{i=1}^{k} p(j_i = 1 | d_i, \theta, U) - \lambda \Delta(D,\theta)$$

Heuristics: consider relevance first, then diversity

Select Top N documents

$$N = (G+1)K$$

Gapped Top K

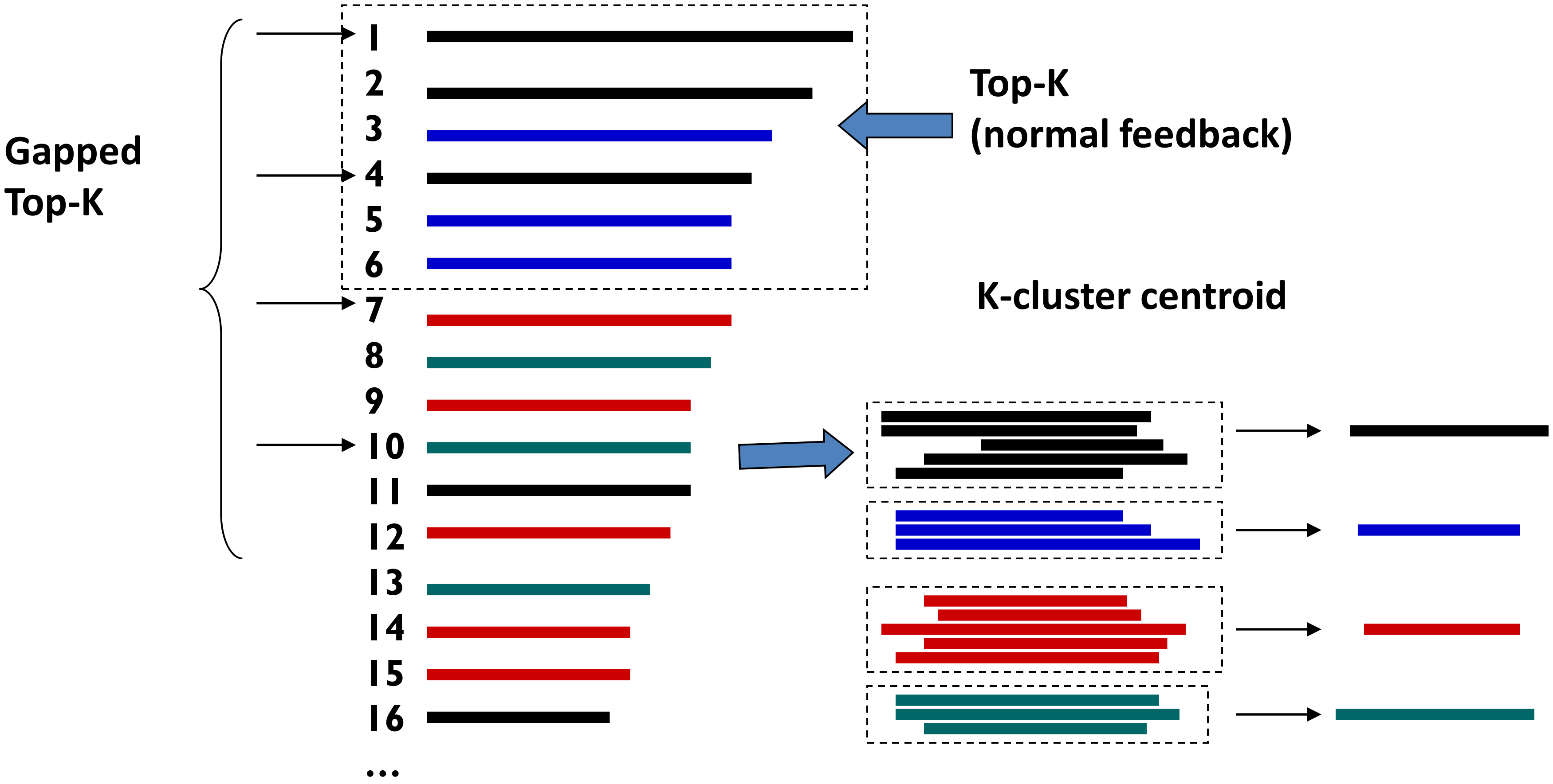
Cluster N docs into K clusters

K Cluster Centroid

…

MMR

Illustration of Three Heuristic AF Methods (K-cluster worked the best)



More principled methods have been developed later (online learning to rank, dynamic IR)

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Whole Session/Page Optimization

- Special case of the IR Game framework: Objective function includes expectation over future interactions
  - Whole session optimization: consider all future interactions with the user
  - Whole page optimization: consider all possible actions a user can take on the page
  - Both directly captured by the Interface Card Model
- Algorithms are generally based on multi-armed bandits and reinforcement learning and aim to optimize the tradeoff between exploitation (optimizing current benefit) and exploration (optimizing future benefit), leading to diversification of results
- The empirical benefit so far has been mostly optimizing the ranking of results, thus no "visible" impact on the interface design
- Exception: **Whole page optimization using ML** [Wang et al. 16]

Yue Wang, Dawei Yin, Luo Jie, Pengyuan Wang, Makoto Yamada, Yi Chang, and Qiaozhu Mei. 2016. Beyond Ranking: Optimizing Whole-Page Presentation. In *Proceedings of WSDM 2016.*

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Why Evaluation?

- Reason 1: Assess the actual utility of a TR system
  – Measures should reflect the utility to users in a real application
  – Usually done through user studies (interactive IR evaluation)
- Reason 2: Compare different systems and methods
  – Measures only need to be correlated with the utility to actual users, thus don't have to accurately reflect the exact utility to users
  – Usually done through test collections (Cranfield evaluation paradigm)

What to Measure?

- Effectiveness/Accuracy: how accurate are the search results?
  - Measuring a system's ability of ranking relevant documents above non-relevant ones
- Efficiency: how quickly can a user get the results? How much computing resources are needed to answer a query?
  - Measuring space and time overhead
- Usefulness: How useful is the system for real user tasks?
  - Doing user studies
- Query-level vs. Session-level vs. Task-level measurement

Challenge in Evaluating IIR Systems

- Problem with using A/B test: Not reusable, not reproducible
- Cranfield evaluation methodology has the following benefit, but it cannot be used to evaluate IIR
  – Reusable test collection → Can be reused and ensure fairness in comparison
  – Facilitate component testing
- How can we make a fair comparison of multiple IIR systems using reproducible experiments?
- Must control the users → Using user simulators!

Simulation as IR evaluation [Zhang et al. 17]

- Benefit
  - "Controlled" user study for reproducibility
  - "Generalized" Cranfield test for sophisticated IR interface
- Goal of the work [Zhang et al. 17]
  - Propose a generalized IR evaluation framework based on search simulation
  - Derive Cranfield tests as a special instantiation case
  - Build simulators for evaluating complex IR interface
- Feasibility shown in some existing work (e.g., [Liu et al. 07], [Carterette et al. 15])

Yinan Zhang, Xueqing Liu, ChengXiang Zhai: Information Retrieval Evaluation as Search Simulation: A General Formal Framework for IR Evaluation. ICTIR 2017: 193-200

Search simulation framework

- Top level components
  - System: S
  - User / simulator: U
  - Task: T
  - Interaction sequence: I
- Metrics
  - Interaction reward and cost: R(I,T,U,S) and C(I,T,U,S)
  - Simulator reward and cost: R(T,U,S) and C(T,U,S)
    - Expectation w.r.t. p(I|T,U,S)

A lap-level decomposition

- Lap level components
  - Lap, user action and interface card
  - User state and user action model
  - Interaction sequence (refined)
    - A series of (user state, user action, interface card) tuples.
- Metrics
  - *Cumulative* reward and cost: $R^t(I,T,U,S)$ and $C^t(I,T,U,S)$
  - Assume to be the sum of lap-level action reward and cost

Cumulative reward and cost

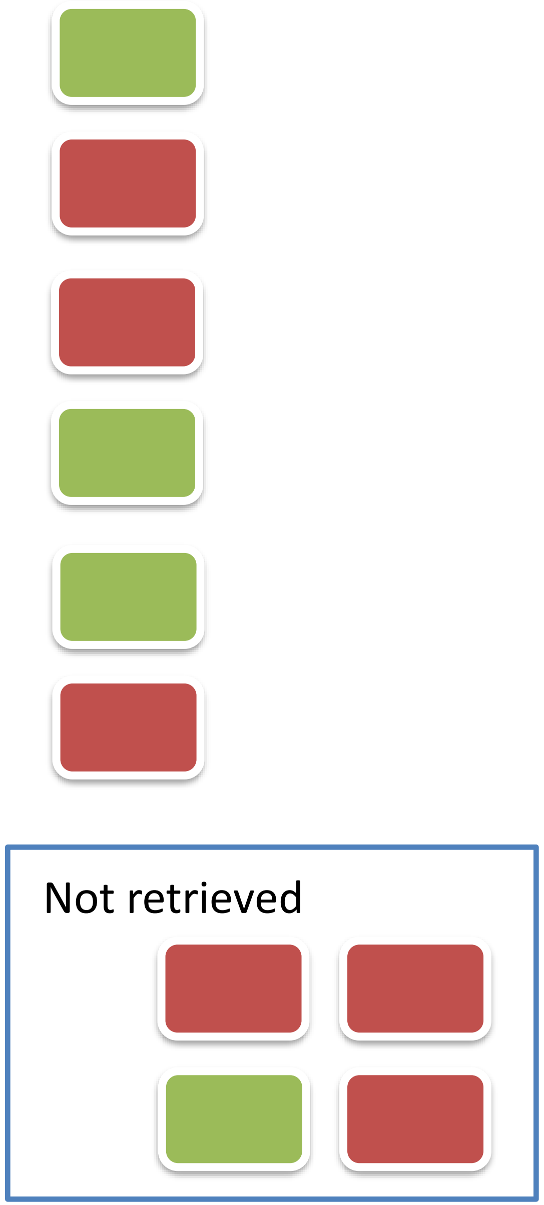
$$R^t(I,T,U,S) = \sum_{i=1}^{t} r(a^i|z^i, q^{i-1})$$

$$C^t(I,T,U,S) = \sum_{i=1}^{t} c(a^i|z^i, q^{i-1})$$

- Remark
  - How to combine the reward and cost measures is application specific
  - The distributions of reward and cost across all interaction sequences are also meaningful

Classical IR simulator

- Task: find (all) relevant documents
- Interface card: document (snippet)
- User action: click / skip (and read next) / stop
  - User always clicks a relevant document
  - User may skip or stop at a non-relevant document
- Lap reward: 1 / 0 for relevant / non-relevant doc
  - Cumulative reward: # relevant docs
- Lap cost: 1 for each doc
  - Cumulative cost: # docs (the simulator scanned through)
- User state: cumulative reward and cost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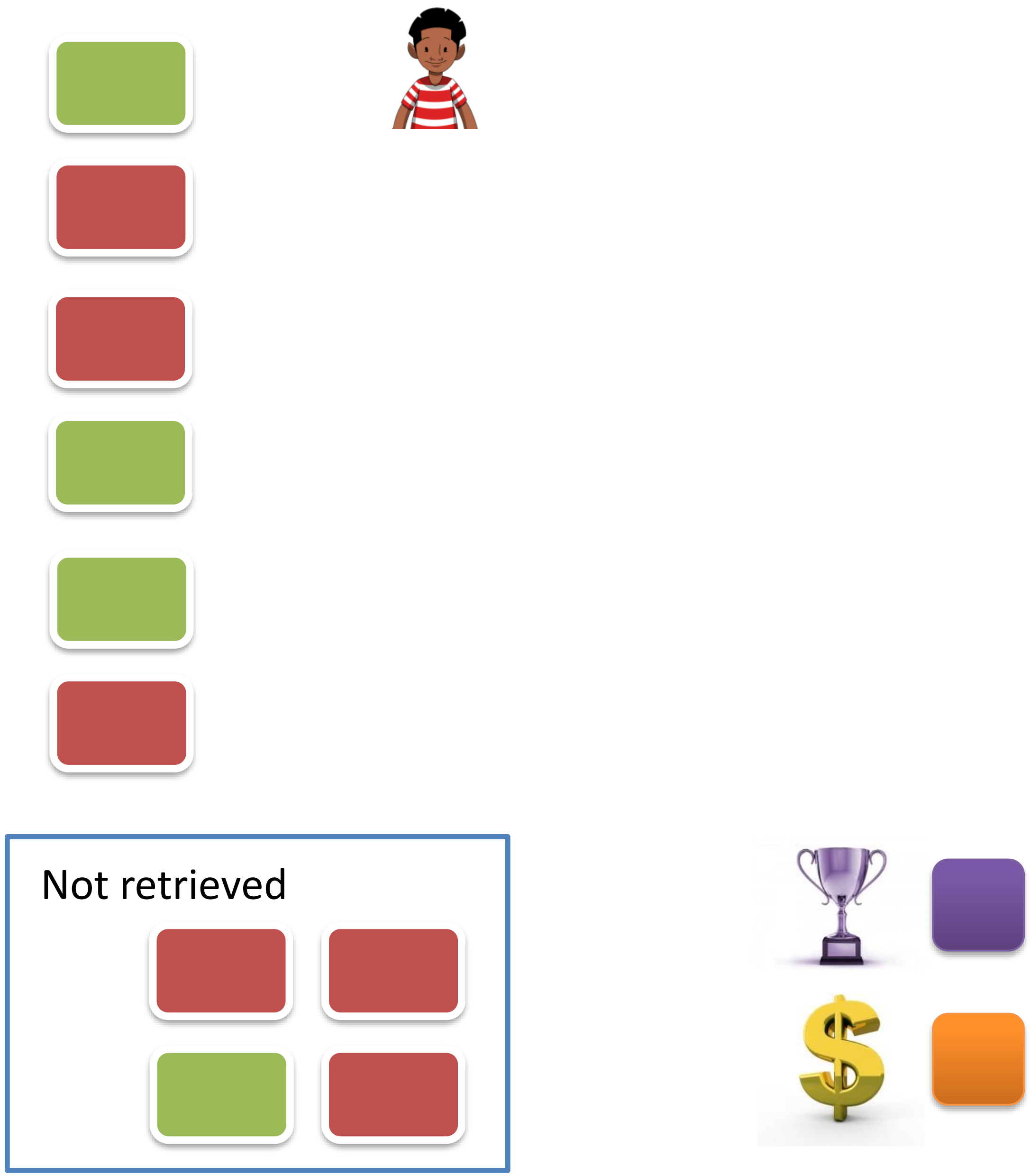
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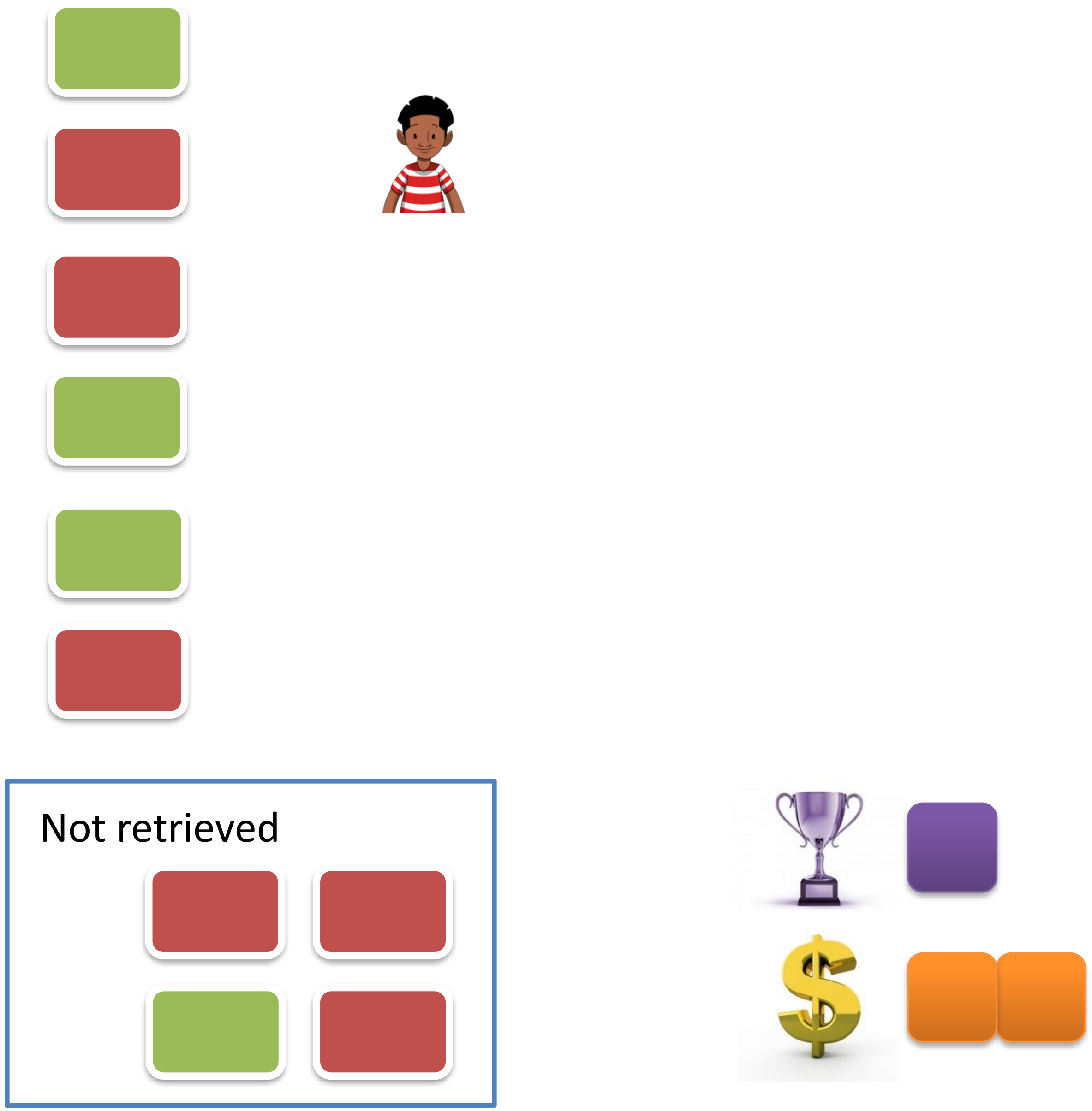
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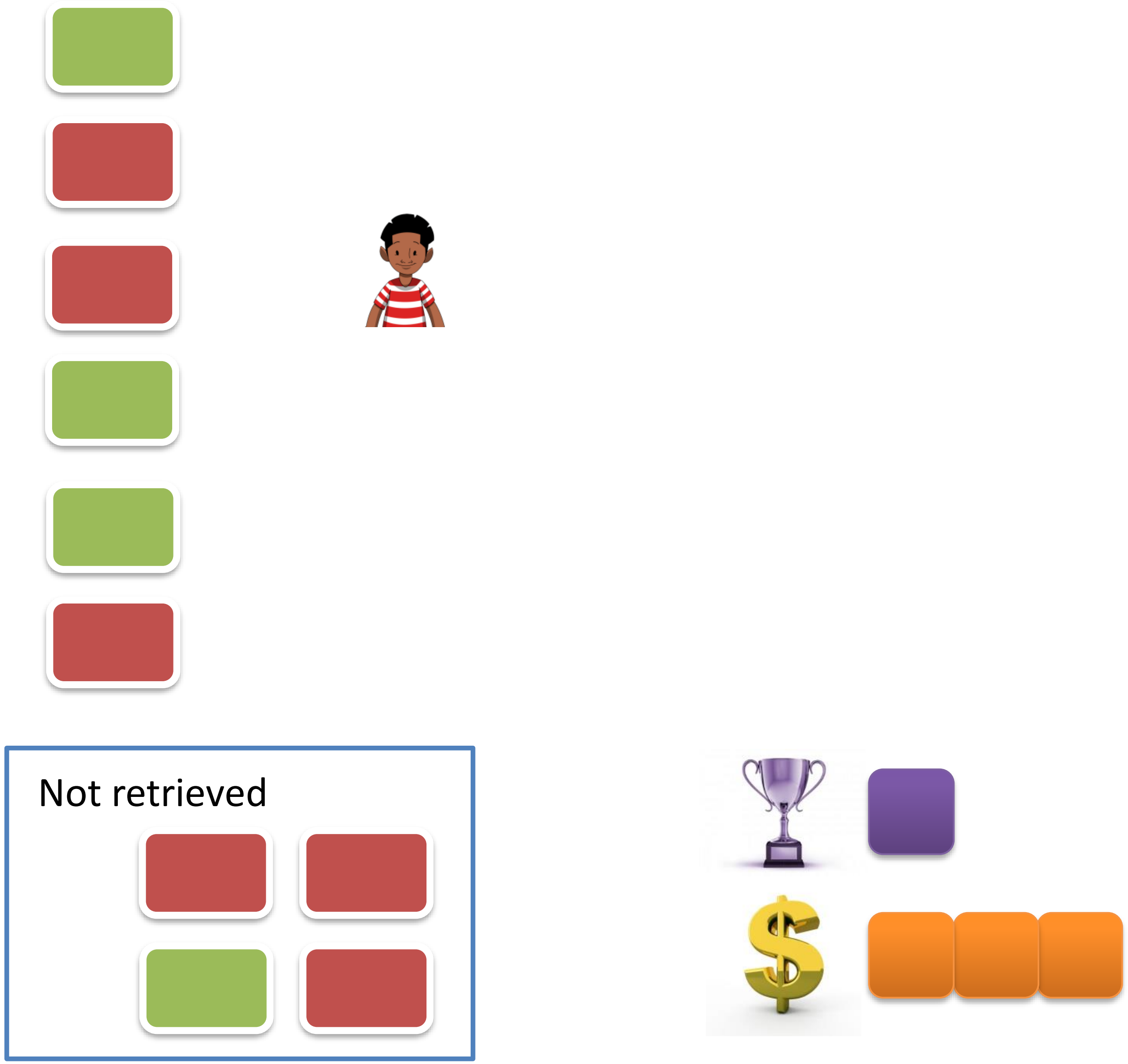
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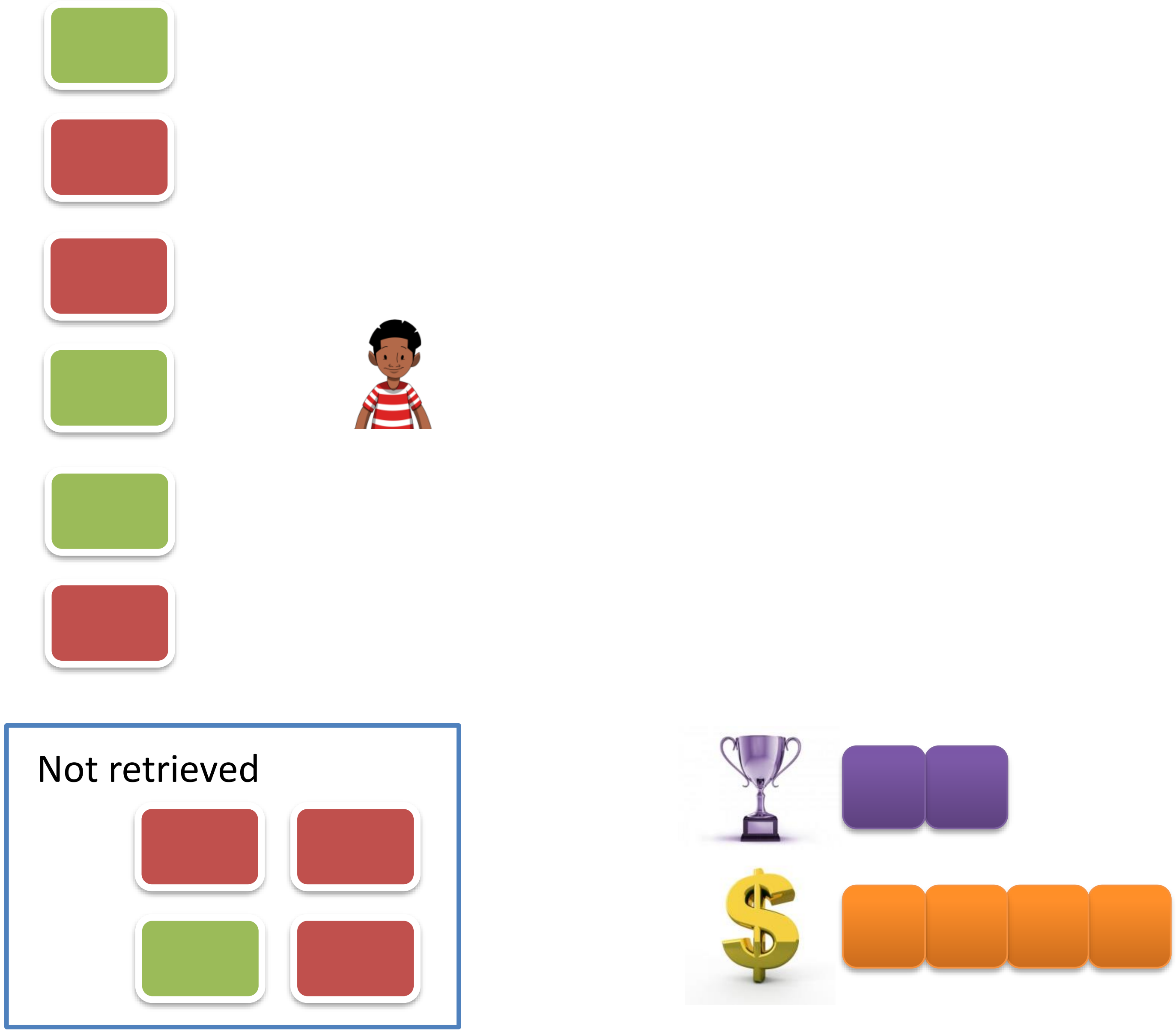
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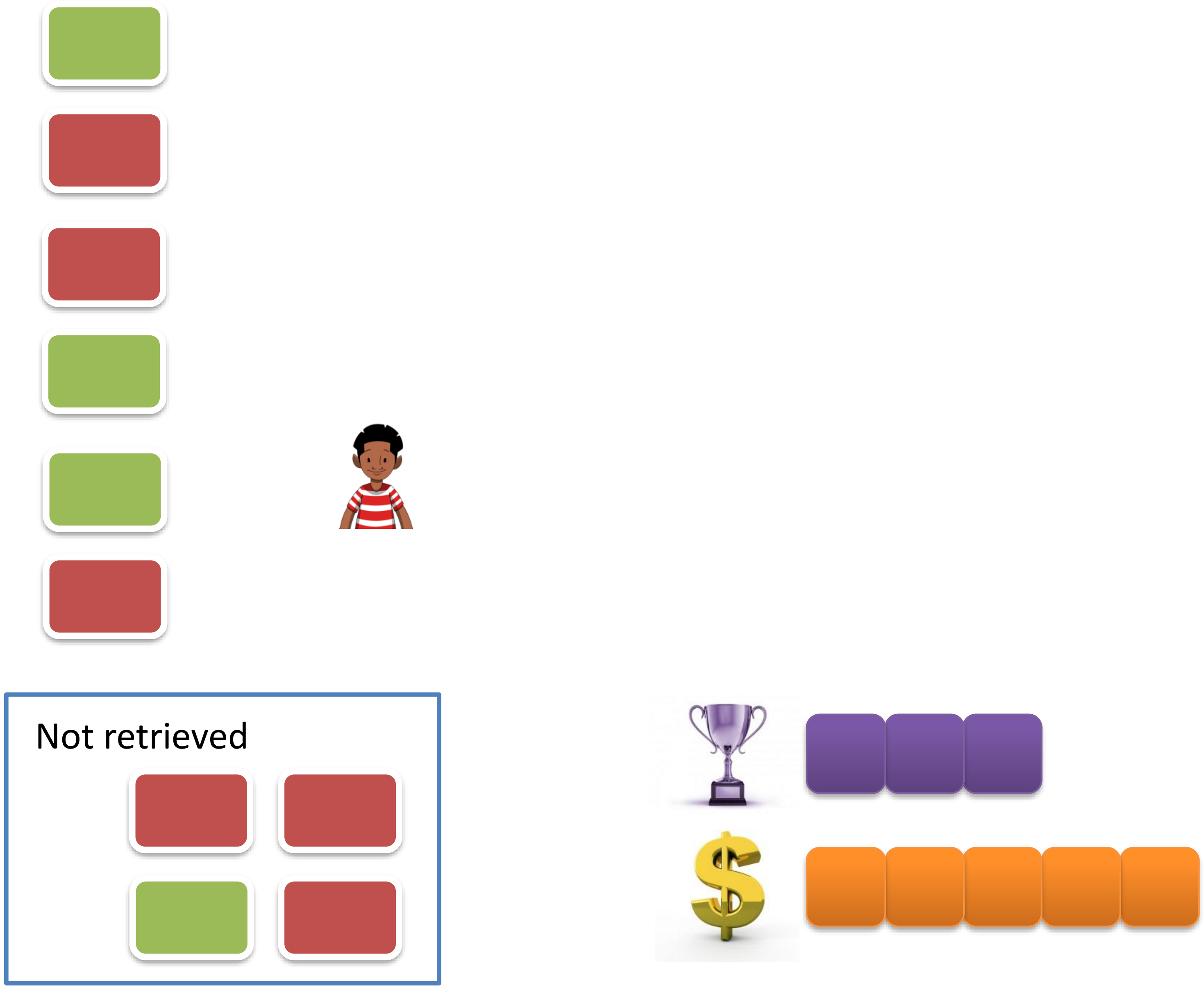
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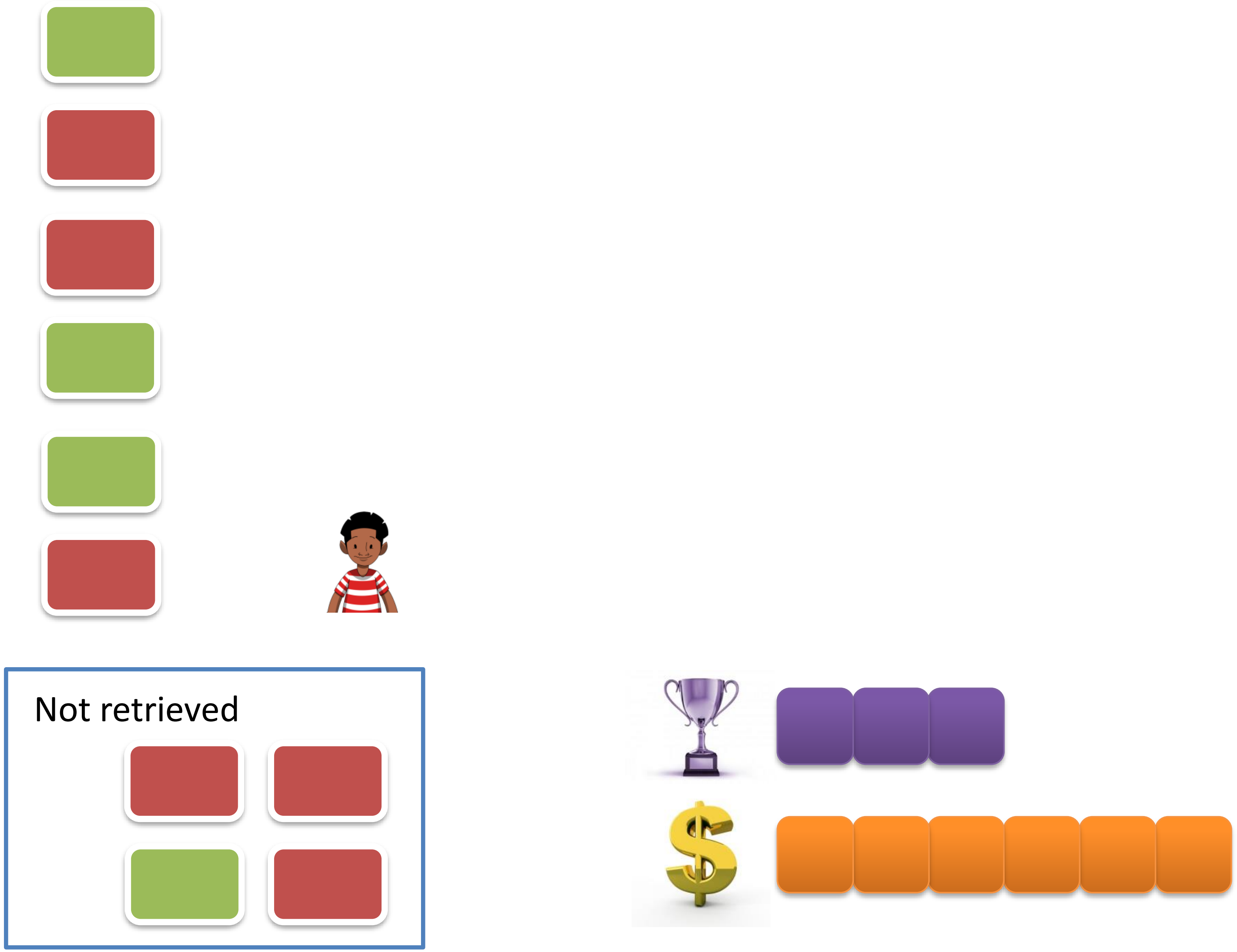
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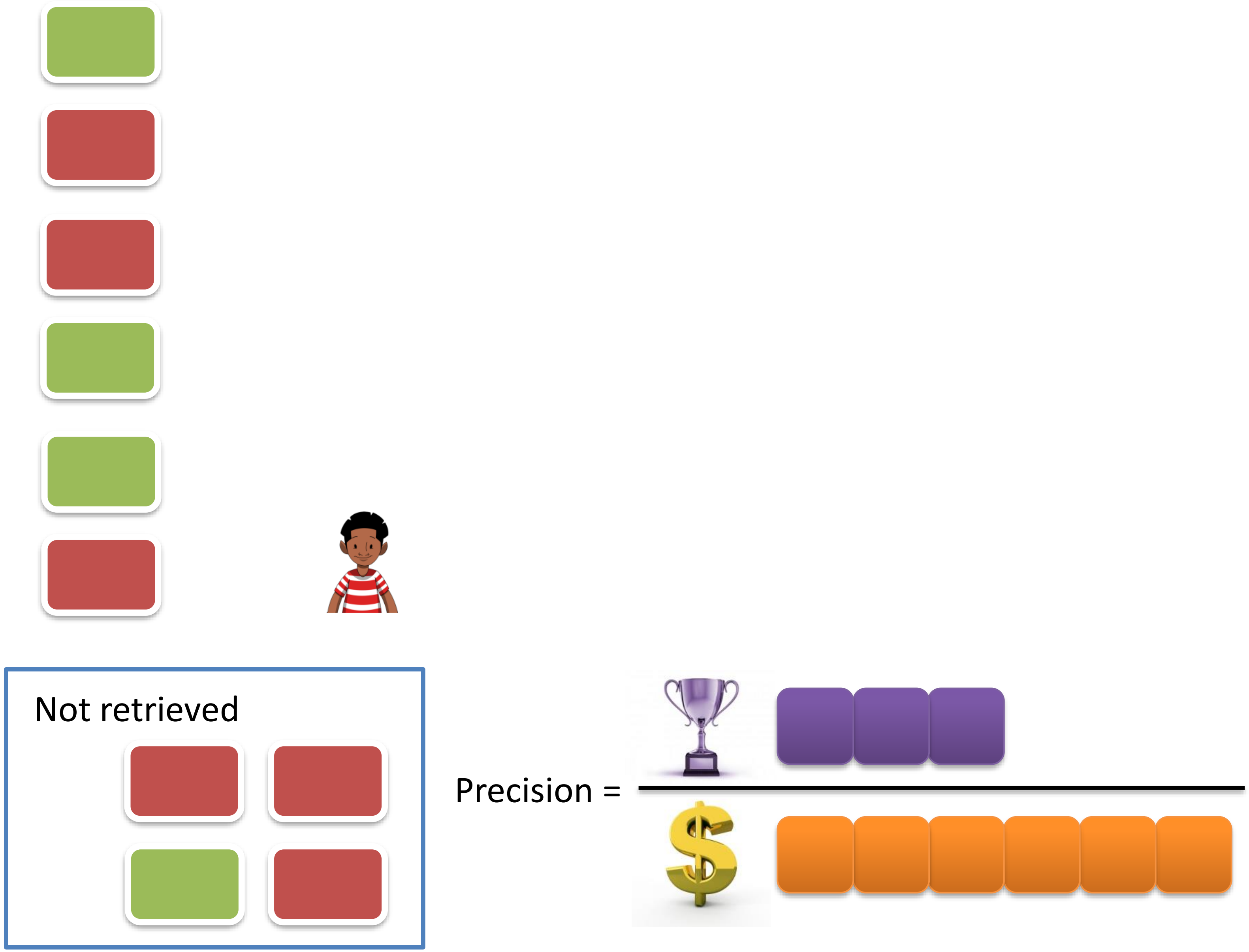
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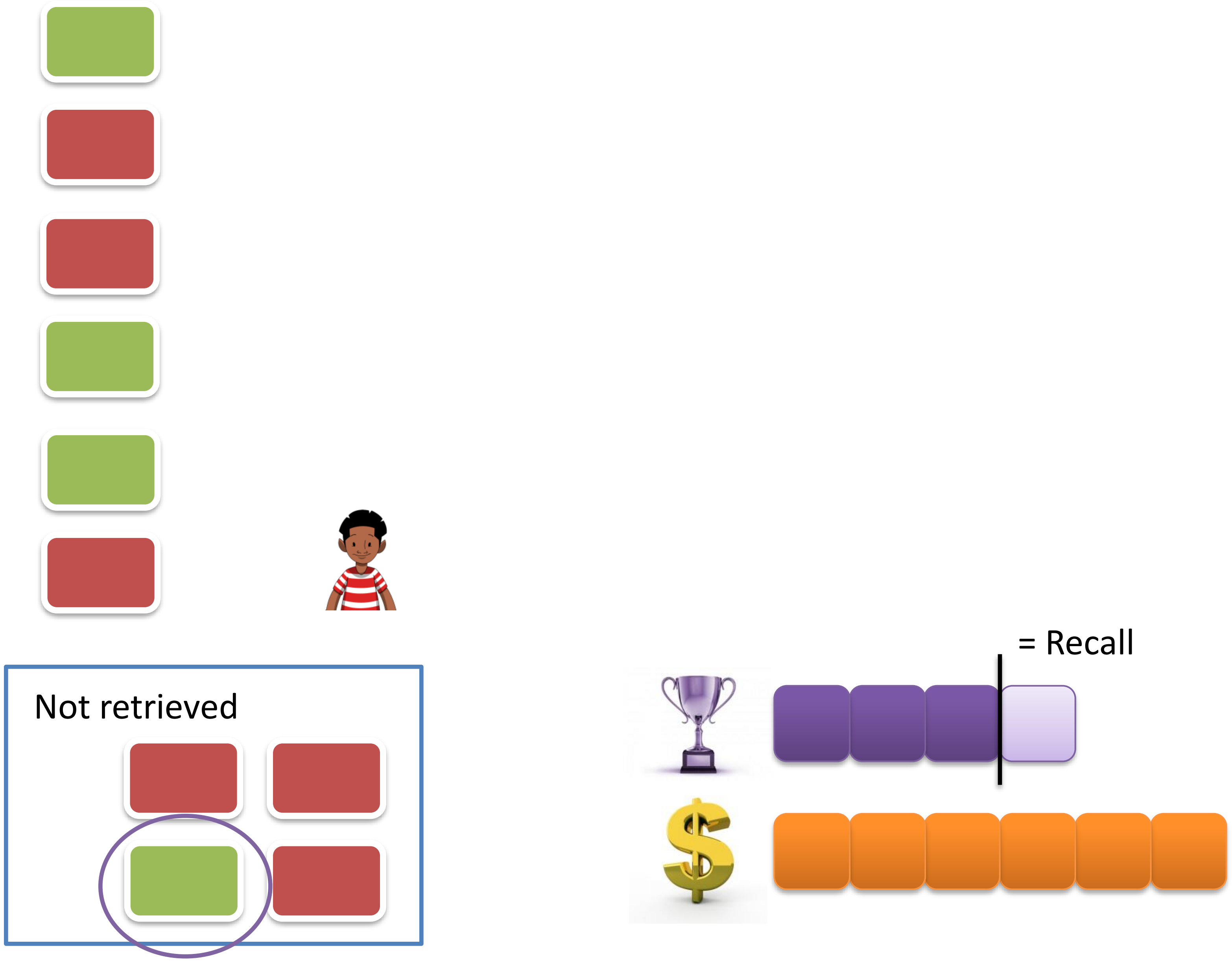
Precision =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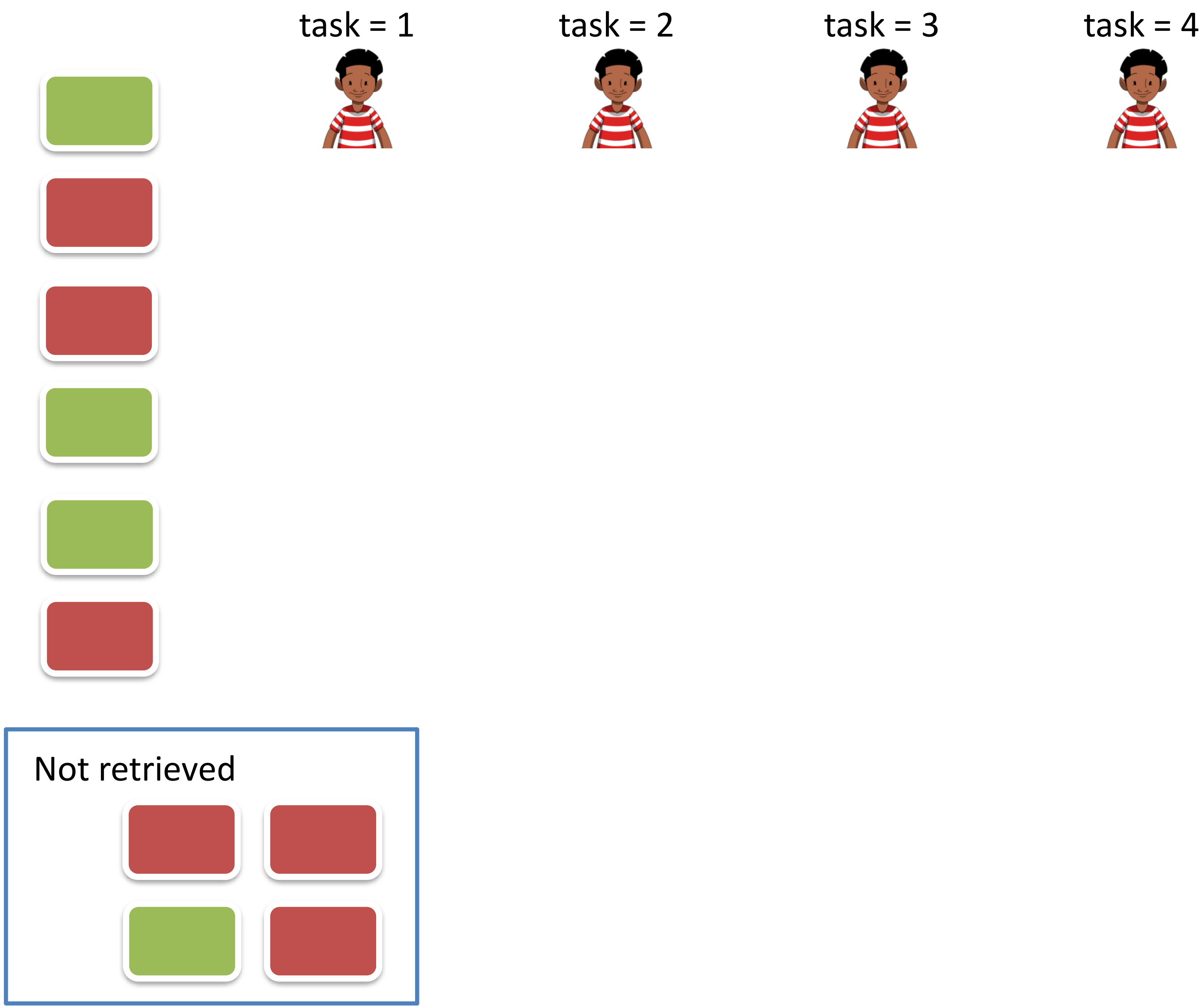
= Recall

Metrics in Cranfield test

- Precision
  - R(I,T,U,S) / C(I,T,U,S)
- Recall
  - R(I,T,U,S) / N, N = maximal possible reward
- Remark
  - Assumes user stops when the list is exhausted
  - Precision@K and Recall@K: K = cost budget
  - Precision emphasizes more on cost; Recall emphasizes more on task completion

Mean Average Precision (MAP)

- Variable-recall simulator
  - Classical IR simulator with task of finding N' relevant documents (N' between 1 and N)
  - Stops and only stops when the task is finished
- Average Precision (AP)
  - Average R(I,T,U,S) / C(I,T,U,S) across N variable-recall simulators with N' ranging from 1 to N respectively
  - AP@K: K = cost budget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task = 2
task = 3
task = 4
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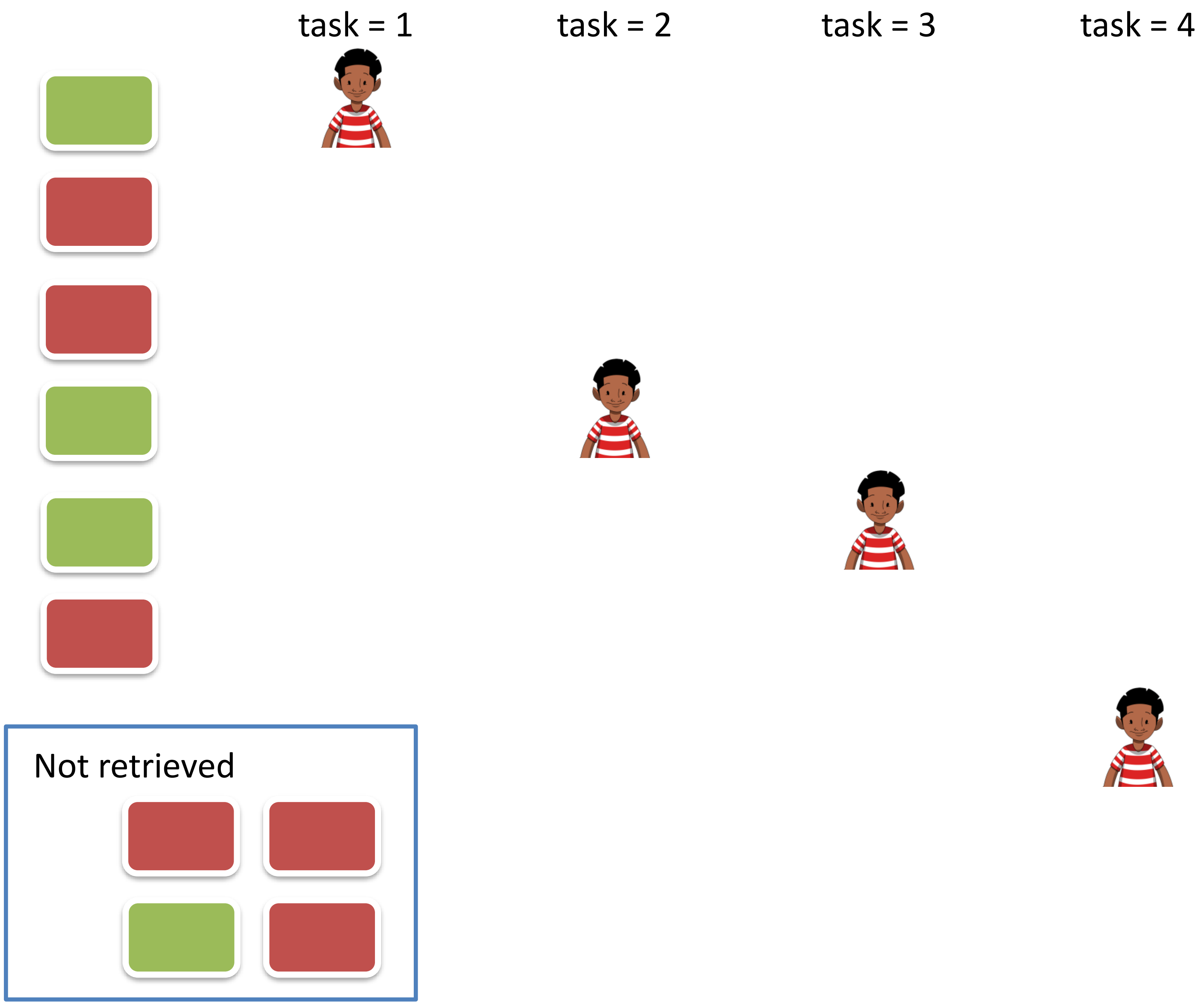
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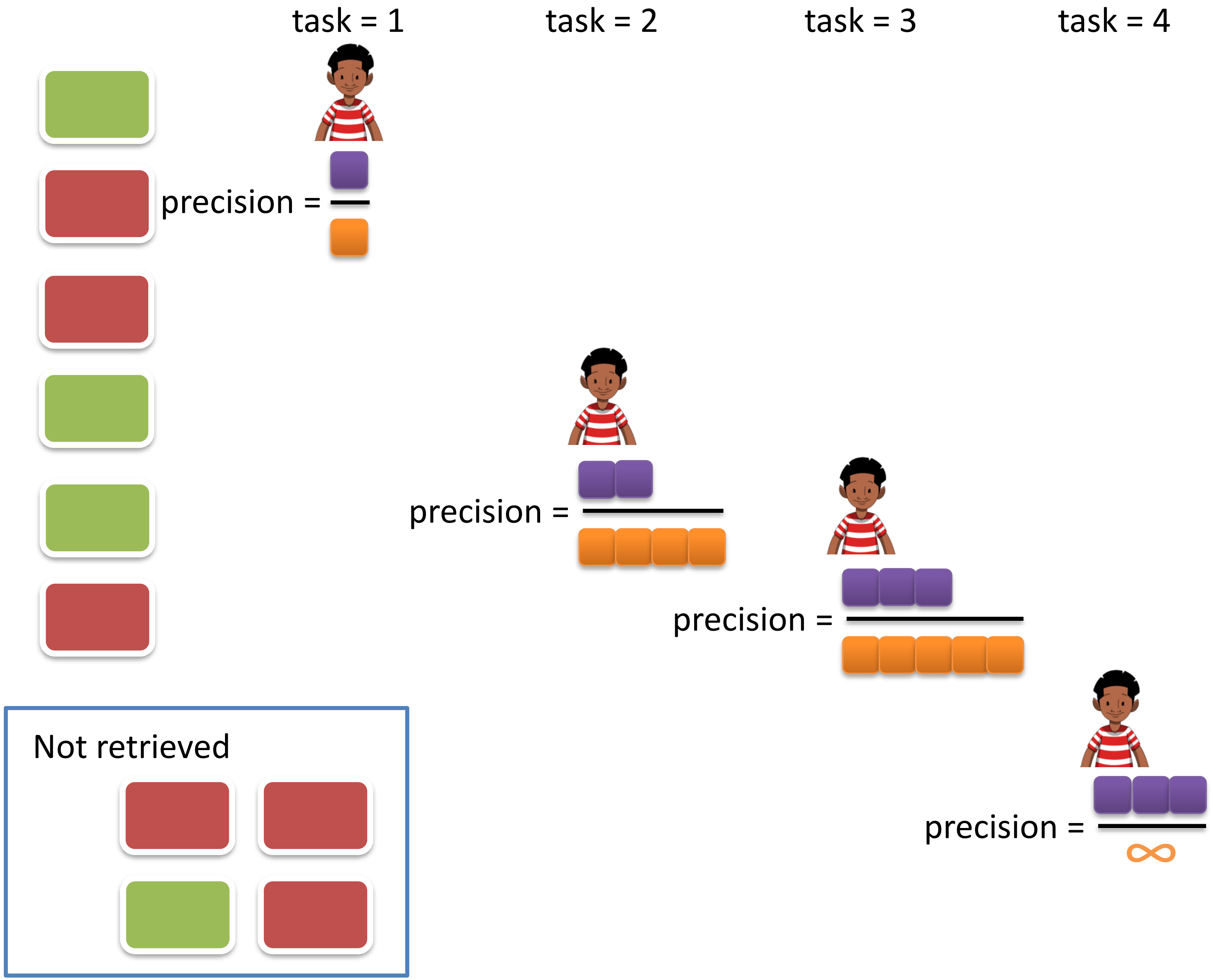
task = 1
task = 2
task = 3
task = 4
precision =
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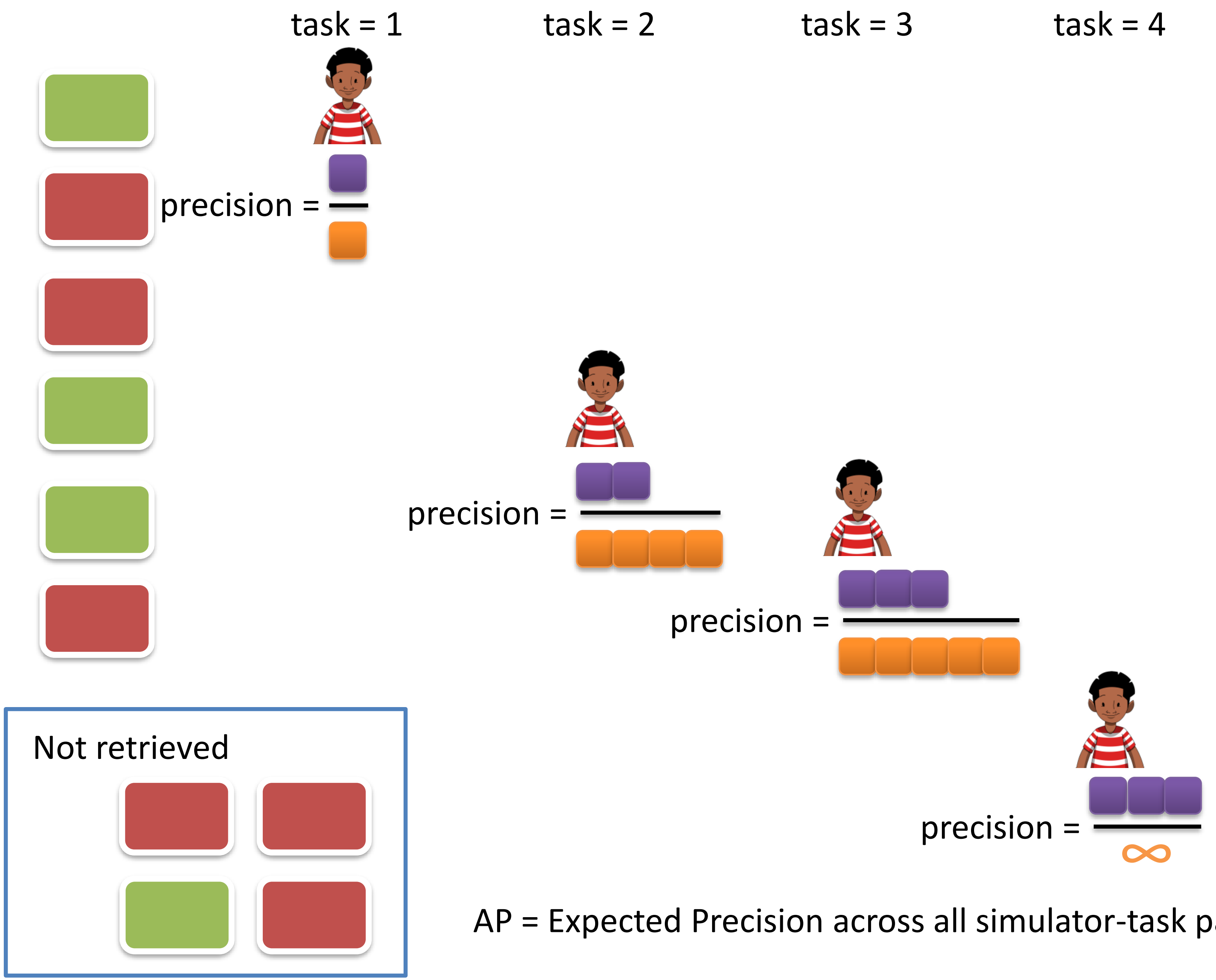

AP = Expected Precision across all simulator-task pairs

Other metrics

- Classical IR
  - Mean Reciprocal Rank (MRR)
  - Normalized Discounted Cumulative Gain (NDCG)
  - Ranked-Biased Precision (RBP) [Moffat & Zobel 08]
  - Time-based gain [Smucker & Clarke 12]
- Session IR
  - Session NDCG
  - U-measure based on trail-text

Tag-based search interfaces

- Example of search interface beyond ranking
  - Traditional interface: static layout
    - Medium screen: tag list alongside document list
    - Small screen: only tag list or document list at a time, and user needs to click "switch" to switch between the two lists
  - ICM interface: dynamic layout
- Evaluation based on simulators
  - Task: find target document(s)
  - Simulator never stops until task is complete
  - Metrics: interaction cost

Tag-based search interfaces: simulator action model

- If a target document is shown, user always clicks it
- Otherwise, if a tag related to a target document is shown, user always clicks it
- Otherwise:
  - On ICM: User always goes to "next page"
  - On medium static interface: user scrolls document list with probability τ, and scrolls tag list with probability $(1-\tau)$
  - On small static interface:
    - If user is on document list, user scrolls list with probability $\tau1$ and switches list with probability $(1-\tau1)$
    - If user is on tag list, user scrolls list with probability $\tau2$ and switches list with probability $(1-\tau2)$

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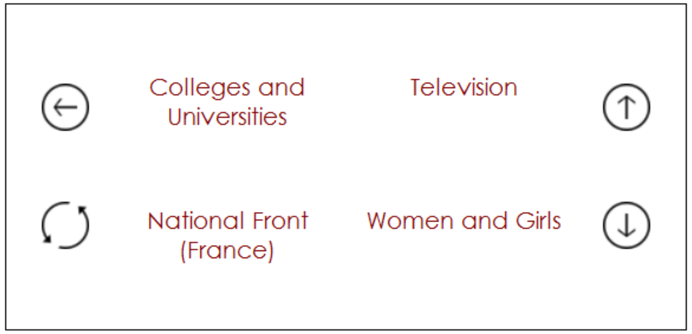


Simulator scrolls list with probability τ_2 and switches list with probability $(1-\tau_2)$

Simulator scrolls list with probability τ_1 and switches list with probability $(1-\tau_1)$

Simulator scrolls document list with probability τ, and scrolls tag list with probability $(1-\tau)$

Figure 6.1: Cost for different document tendency values (τ) on medium screen with static interface

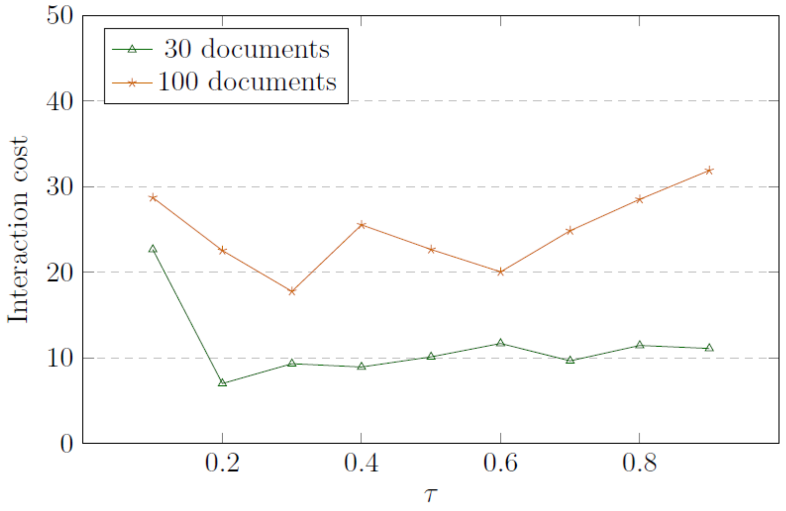
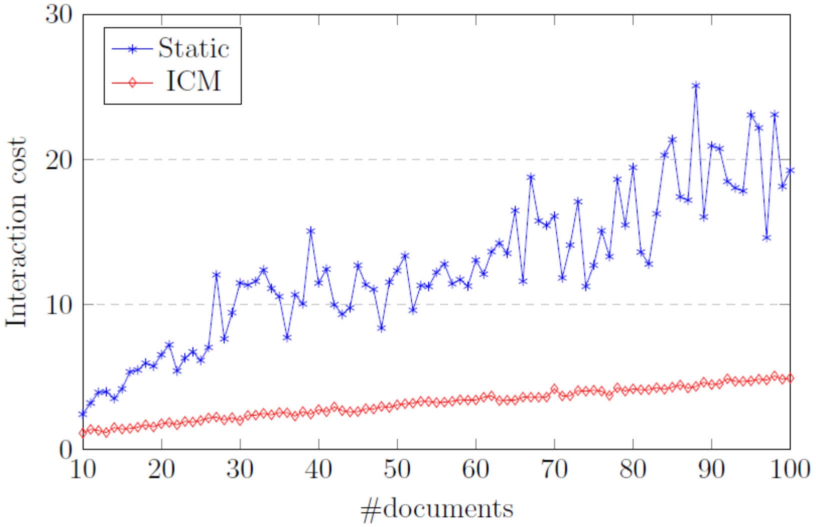


Figure 6.2: Cost comparison for medium screen



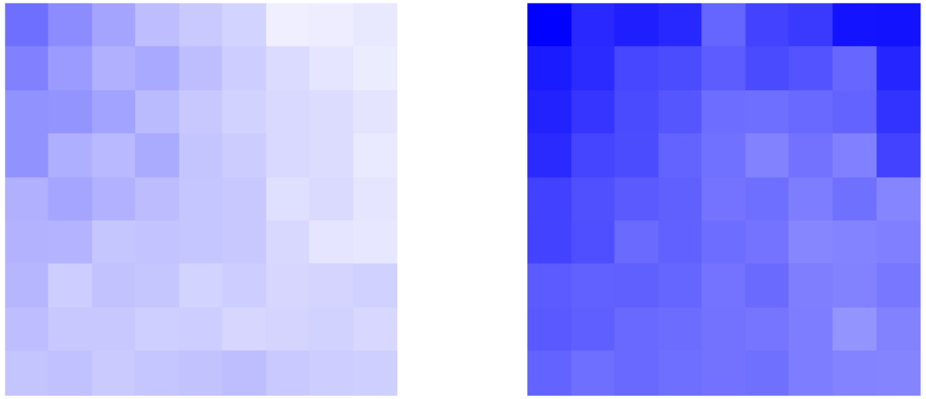
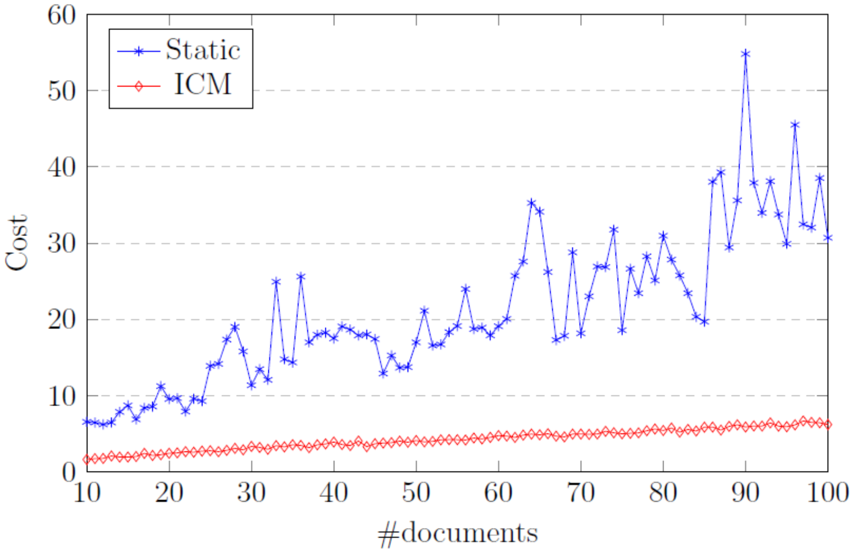


Table 6.1: Heat maps of cost for different document inertia (τ_1) and tag inertia (τ_2) values on small screen w/ static interface. Left: #documents = 30. Right: #documents = 100. In each heat map - top to bottom: $\tau_1 = 0.1$ to 0.9; left to right: $\tau_2 = 0.1$ to 0.9.

Figure 6.3: Cost comparison for small screen



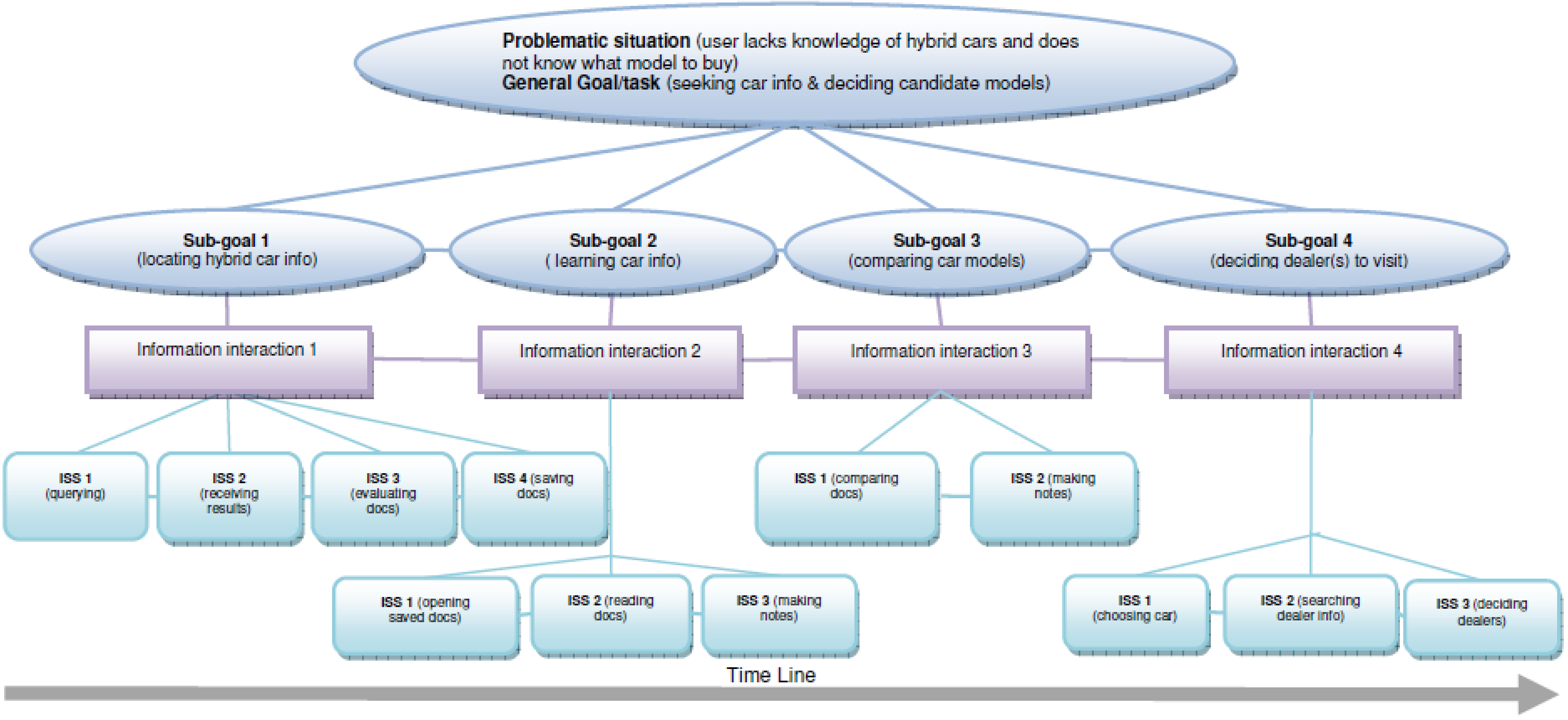
Validation from real user experiment

- Real user experiment
  - ICM is more efficient than static interface
  - The difference is higher on small screen than on medium screen
- Insights about real user behavior
  - Users can well utilize the tag list on the medium screen, but cannot make full use of the tag list on the small screen

Screen size	Sample size	Workers' average
Small	42	$\hat{\tau}_1 = 0.845$, $\hat{\tau}_2 = 0.370$
Medium	38	$\hat{\tau} = 0.211$

Table 6.2: Real user action averages

Nick Belkin's Model for IR Evaluation



Evaluation based on the following three levels:

1. The usefulness of the entire information seeking episode with respect to accomplishment of the leading task;
2. The usefulness of each interaction with respect to its contribution to the accomplishment of the leading task;
3. The usefulness of system support toward the goal(s) of each interaction, and of each ISS.

Nicholas J. Belkin, Michael Cole, and Jingjing Liu, A Model for Evaluation of Interactive Information Retrieval, SIGIR Workshop on the Future of IR Evaluation, July 23, 2009, Boston.

Other Related Evaluation Work

- Evaluation-as-a-Service (EaaS): Send algorithms to where the data are (i.e., Algorithm-to-Data instead of Data-to-Algorithm)
  - Can be generalized to support evaluation based on user simulators
- Living Lab (Online Evaluation): Participating systems are connected with a “living lab” via an API, and the systems are evaluated by showing their results to real users.

Rolf Jagerman, Krisztian Balog, Maarten de Rijke: OpenSearch: Lessons Learned from an Online Evaluation Campaign. J. Data and Information Quality 10(3): 13:1-13:15 (2018)

Frank Hopfgartner, et al. Evaluation-as-a-Service for the Computational Sciences: Overview and Outlook. J. Data and Information Quality 10(4): 15:1-15:32 (2018)

Summary

- IR is generally an interactive process → **IIR = general model of IR**
- Research in IIR is **highly interdisciplinary**: CS (HCI) + IS (HII)
  - Research remains mostly scattered in different communities
  - Applications are driving integration of scattered research slowly
  - General formal frameworks would accelerate integration
- **IR Game** as a **general formal framework for IIR:** Optimization of human-computer collaboration with the shared goal of helping users finish a task while minimizing their overall effort (and minimizing system operation cost)
  - **Optimization** of **4 C**'s: **Collaboration, Communication, Cognition, and Cost**
  - **Mathematically model everything** about the user and the retrieval situation
  - **Adaptively optimize responses** to **user actions** over the **horizon of all future user actions and system responses**
  - Ties separate lines of research in a single **unified framework**

Summary (cont.)

- Research so far has only very limited success
  - Success: Promising technical tools have been developed and proven beneficial: MDP/POMDP, Stochastic Games, Reinforcement Learning, Economics
  - Limitations:
    - **Limited view of IIR**: Basic search model =**simplest IR game**
    - Impact has so far been mostly on improving ranking accuracy (with a traditional simple search interface) with **no/little improvement of the design of interface or suggestion of new interface/interactions**

Major Challenges for Future Research

1. **How to evaluate an IIR system (with controlled experiments)?**
   – How to build realistic user simulators? User search logs? User study designed specifically for eliciting user behavior?
   – How to measure task performance and measure user effort?
   – How to incorporate "retrieval situation" (retrieval context) into an evaluation framework?
2. **How to formally (mathematically) represent and model a user?**
   – How to leverage theory from Psychology to design a formal user model?
   – How to represent a user's state of knowledge? Formally define the anomalous state of knowledge (ASK)?
   – How to model many other aspects of a user (e.g., search style, browsing behavior, situational constraints, cognitive state, …)
   – How to model shared characteristics of users? Structure on users?

Major Challenges for Future Research (cont.)

3. How to infer and update a user model over time?

- Given all the observed data about a user, how can we infer knowledge about the user and update the user model over time?
- How can we recognize and correct errors in a user model (misunderstanding of users)?

4. How to define and model a user's task?

- What is exactly a user task?
- How do we assess whether a user task has been completed? Assess progress toward task completion?
- How do we go beyond supporting query formulation to task specification?

Major Challenges for Future Research (cont.)

5. How do we design an "IR game" with richer user actions and system responses?

- How can we systematically enumerate the possibilities of "interface cards"? Are there a finite number of basic interface elements that would be sufficient when combined in a flexible way?
- How can we design interfaces to encourage/optimize user-system collaboration? (**Interface = Language for communication between users and system**)
- How do we design interfaces to enable multi-mode interactions (e.g., speech + touch screen)?
- How can we design interfaces to enable a system to explain its responses to users?
- How can we parameterize an interface to enable automated optimization of interface using an algorithm?

6. How should we formalize the optimization problem of IIR?

- How do we formally define the multiple objectives (task performance, user effort, system cost, …)?
- How do we set up the optimization problem so as to make it feasible to solve it?

Major Challenges for Future Research (cont.)

7. How can we efficiently solve the optimization problem of IIR?

- POMDP and reinforcement learning are generally complex to compute. How can we simplify the objective function and make approximations?
- How can we leverage advances in machine learning to improve modeling and algorithms for IIR?
- How can we engage users to help simplify the optimization problem (resolve uncertainties)? How to simplify the exploration-exploitation tradeoff?

8. How can the system dynamically adapt the interface to each individual user in a context-sensitive and task-sensitive way?

- Novice vs. expert users?
- Search while sitting in a train vs. being at home?
- Medical diagnosis task vs. search to help solve a homework problem?
- How can the system adapt the interface while minimizing the cognitive load on users? How can the system "train" a user to recognize changes in the interface?

Major Challenges for Future Research (cont.)

9. How can the system provide help for users all the time?

– Many “help me to do X” buttons?

– “Reporting problem” button on every interface page?

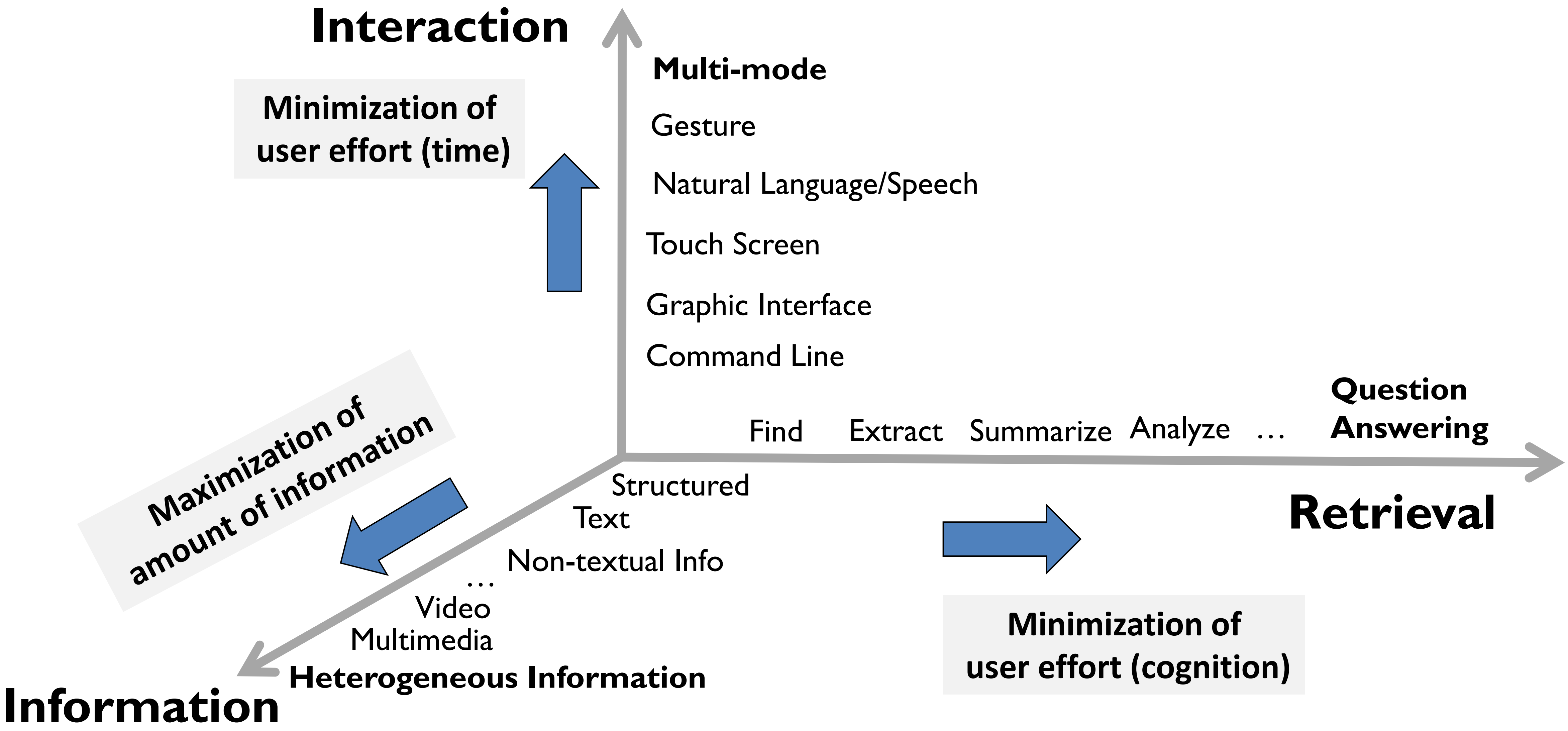
– How to maximize the flexibility for a user to dynamically reconfigure an interaction interface (let the user “program” the interface)?

– How to sense a user’s emotion during IIR? How to detect “struggling” state of a user?

10. How to support multi-mode interactions and go beyond search to support user tasks?

– Opportunities to both leverage advances in HCI and contribute to HCI

Future of Interactive Information Retrieval



Thank You!

Questions/Comments?

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Note: the references are inevitably incomplete due to the breadth of the topic; if you know of any important missing references, please email me at czhai@illinois.edu.

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